ADAPTATION BASED ON LEARNING STYLE AND KNOWLEDGE LEVEL IN E-LEARNING SYSTEMS

by

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Abstract

Although there have been numerous attempts to build and evaluate adaptive e-learning systems, they tend to be limited in scope, and suffer from a lack of carefully designed and controlled experimental evaluations of their effectiveness and usability. This thesis addresses these issues through the implementation of an adaptive e-learning system and its experimental validation. The design of an adaptive framework and the specific instantiation of its components into a configurable adaptive e-learning system are presented. The domain model of the system deals with computer security. The learner model incorporates the information perception dimension of the Felder-Silverman model of learning style and also knowledge level. The adaptation model generates personalised learning paths and offers adaptive guidance and recommendation.

The thesis also provides an empirical evaluation through three controlled experiments to investigate the effect of different forms of adaptation. Rigorous experimental design, careful investigation and precise reporting of results are taken into account in all the three experiments. The findings indicate that matching the sequence of learning objects to the information perception learning style yields significantly better learning outcome and learner satisfaction than non-matching sequences. They also indicate that adaptation based on the combination of the information perception learning style and knowledge level yields significantly better learning outcome (both in the short- and long-term) and learner satisfaction than adaptation based on either of these learner characteristics alone; this combination is also marked by a significantly higher level of perceived usability compared to a non-adaptive version of the e-learning system.

Dedication

To my Father

To my Mother

To my wife

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Chapter 1. Introduction

1.1 Overview

Teaching has shifted from an instructor-centric approach, which focuses mainly on transmitting knowledge from expert to learner, to a learner-centric approach, in which knowledge is constructed by learners who are actively involved in the learning process and are engaged in collaborative work with their peers [Vrasidas 2000]. E-learning systems are expected to support better learner-centric instruction and enable more self-paced and self-directed learning [Anderson 2008]. E-learning can be generally defined as "the use of the Internet to access learning materials; to interact with the content, instructor, and other learners; and to obtain support during the learning process, in order to acquire knowledge, to construct personal meaning, and to grow from the learning experience" [Ally 2004]. E-learning systems remove distance barriers to education as learners may be spread across widely separated geographical areas. A large number of free, open-source and commercial e-learning systems already exist [Hauger and Köck 2007]. They have been developed and used by several organisations such as universities, schools, and even in business and military sectors to support learners and to manage learning programmes.

There are, however, several issues regarding learner-system interaction with traditional e-learning systems [Hauger and Köck 2007; Shute and Towle 2003; Welsh et al. 2003]. In most systems, the diversity of learners is not often taken into account to a sufficient degree [Hauger and Köck 2007]. People differ in personalities, abilities, experiences, skills, learning styles and preferences. Traditional e-learning systems do not generally take these characteristics into account and do not provide truly personalised and adaptive learning [Brusilovsky 2012]. E-learning systems may successfully retrieve a variety of learning material and resources that technically match a specific query or goal, but they usually fail to provide the most relevant learning material that meets the needs of individual learners [Hauger and Köck 2007]. Instead, learners have to explore, filter and organise a large amount of material; they must focus on system functionality instead of the learning which is their primary task. In addition, a large volume of information may overwhelm learners during the process if they do not know when, where and what to study. This makes it difficult to process information, leading to less effective learning. Traditional e-learning systems tend to provide the same courses and similar learning material in the same sequence to all users, which may be problematic and lead to learner dissatisfaction and increased dropout rates [Sun et al. 2008].

Adaptation is often put forward as a way of tailoring a system to the user's requirements [Brusilovsky 2012]. Adaptive e-learning systems integrate learner characteristics such as learning style, affective state, skills and knowledge level to provide personalised services, and to recommend relevant instructional material; they are an enhancement to the dominant, one-size-fits-all approach to the development of e-learning systems. A system may highlight appropriate information, recommends what a given learner studies, or constructs personalised learning paths [De Bra and Calvi 1998; Kavcic 2004].

Since this thesis presents research concerning adaptation in e-learning systems in which learning material can be personalised and appropriately sequenced to meet the needs of individual learners, it takes a cross-disciplinary approach that draws from the fields of education and computer science. The specified research questions in this thesis are best answered by combining the theoretical concepts and best practices of these two disciplines; taking each field in isolation is not adequate [Joy 2004].

From the field of education come several theories and models of learning, such as behaviourist, cognitivist and constructivist theories [Ertmer and Newby 1993]. It is crucial when designing and implementing e-learning systems to identify how people learn. Understanding the different characteristics of learners is also important in order to meet their requirements. Amongst learner characteristics, learning style and learner knowledge are recognised as important factors in learning [Felder and Silverman 1988; Essalmi et al. 2010]. Learning style is the way in which a learner obtains or perceives information in a learning environment to be processed in a cognitive structure for meaningful information connection and retention in memory [Keefe 1979]. Many educational theorists agree that taking learning style into account in instruction can improve learning [Felder and Silverman 1988; Keefe 1979; Pashler et al. 2008; Dunn et al. 1995]. It is also argued that if a learner has a strong affinity with a particular learning style, the instructional material should match this style to enhance learning [Felder and Silverman 1988]. Learner knowledge is also a fundamental learner characteristic that should be taken into account in systems to enhance learning; it describes the extent to which a learner understands, applies and recalls specific information related to a particular topic [Papanikolaou et al. 2003; Klasnja-Milicevic et al. 2011]. The characteristics of learning style and learner knowledge are central to this research.

In the computer science field, personalisation and adaptation of e-learning systems remains an important issue for researchers. Learner modelling is an important aspect in adaptive e-learning systems; it is concerned with the way learner characteristics such as learning style, affective state, skills and learner knowledge are represented, stored and maintained [Chrysafiadi and Virvou 2013b]. The development of adaptive methods and techniques represents an important concern in adaptive e-learning systems. These techniques specify the way that information is presented and sequenced to meet the needs of learners. One focal point of research relates to the development of adaptive models and frameworks which aim to facilitate the implementation of adaptive systems; the frameworks incorporate important components that are necessary to provide adaptation such as the domain model, the learner model and the adaptation model. Another aspect of research is concerned with domain models that store and represent learning material in a way that facilitates the process of adaptation. Domain modelling also deals with the design and implementation of content authoring tools for adaptive e-learning systems [Stash et al. 2004].

This chapter introduces the motivation of this work and relevant background. It also outlines the research questions that are investigated. It then specifies the research methodology, highlights the contribution of this research, and presents a list of peer-reviewed publications which resulted from this work. The structure of this thesis which makes up the rest of the chapters is also provided.

1.2 Background and Motivation

The provision of educational environments and content that take into account individual characteristics such as learning preferences, abilities, skills and knowledge is referred to as personalised learning or adaptive instruction [Park and Lee 2003]. Adapting instructional material and its delivery represents a fundamental role in enhancing learning; adaptive instruction can be traced back several centuries [Snow 1977]. Adaptive instruction can be applied in classes to facilitate the differentiation of teaching approaches to meet the needs of learners [Shute and Towle 2003]. As an approach to providing adaptive instruction based on knowledge level, each learner may, for instance, be assessed by a pre-test that leads to the assignment to a specific instructional unit. Upon completion of each unit a post-test is provided to determine the learner's knowledge level of the material. The learner is required to achieve a satisfactory level on the completed unit before proceeding to the next appropriate unit. However, adaptive instruction in traditional classroom settings is limited because of the large numbers of students and the limited class time available [Brusilovsky et al. 1998]. Teachers may not always have the time, the resources and the ability to assess, for instance, the knowledge level of each learner and to modify their teaching approaches accordingly [Pask 1976].

With the advent of computer technology, networking and the Web, many e-learning systems were developed to provide learning environments that help learners access learning material and interact with their teachers and other learners. These systems remove the distance barriers to education by offering learning opportunities anytime and anywhere. However, as mentioned earlier, traditional e-learning systems often provide the same learning material, the same presentation and sequence for all learners irrespective of their characteristics such as learning style, affective states, abilities and knowledge levels.

Adaptation is often put forward as a way of tailoring the presentation of learning material and its sequencing in e-learning systems to meet the requirements of the learner [Brusilovsky 2012]. Many adaptive e-learning systems have been developed; they are inspired by work in both the intelligent tutoring system (ITS) and adaptive hypermedia or web-based educational fields [Park and Lee 2003]. ITSs are adaptive educational systems developed with the application of artificial intelligence techniques such as decision trees, fuzzy logic and Bayesian networks to create virtual one-on-one teaching [Self 1999]. In the early 1990s, the development of adaptive hypermedia or web-based educational systems began to meet the requirements of the increased number and variety of learners who had personal computers to access information on the Web. The ultimate goal of adaptive e-learning systems is to personalise learning material and its sequencing, to match the needs of an individual learner as closely as possible in order to enhance learning. These systems integrate learner characteristics such as learning style, skills, abilities, affective state and knowledge level to provide personalised services and recommend relevant instructional material [Brusilovsky 2001; Brusilovsky 2012].

As mentioned earlier, learning style and learner knowledge are recognised as important factors in learning [Felder and Silverman 1988; Essalmi et al. 2010]. Many adaptive e-learning systems that incorporate learning style, learner knowledge or a combination of the two have been developed [Alshammari et al. 2014; Essalmi et al. 2015; Hauger and Köck 2007]. ELM-ART was one of the first and most influential [Brusilovsky et al. 1996; Weber and Brusilovsky 2001]. Despite dating from 2001, it remains in use today for learning Lisp programming; it adapts learning material according to the learner's knowledge level [Weber and Brusilovsky 2015]. CS383 is also an early system that personalises learning material related to a computer systems course, based on learning style [Carver et al. 1999]. MASPLANG is a pioneer in the area, combining both learning style and knowledge level to adapt learning material related to a computer networking course [Peña et al. 2002]. INSPIRE is a popular and important example; it is an intelligent system based on learning style and knowledge level that personalises instruction related to a computer architecture course in an online environment [Papanikolaou et al. 2003].

One recent successful example is Protus [Klasnja-Milicevic et al. 2011], an adaptive e-learning system based on learning style and learner knowledge that recommends relevant learning material in the teaching of the Java programming language. The TSAL system takes into account learner interactions with the system and learning style in order to recommend relevant learning material related to mathematics [Tseng et al. 2008]. Limongelli et al.

developed the LS-Plan system, integrating both knowledge level and learning style in order to generate personalised learning paths for users [Limongelli et al. 2009].

It is not always evident how to incorporate adaptation into e-learning systems in general and, more particularly, into adaptation based on learning style [Brusilovsky and Millán 2007]. In addition, when learning style is taken into account in adaptive e-learning systems, it is rarely combined with other learner characteristics such as learner knowledge to provide adaptation; moreover, these initiatives are rarely followed by a high quality and thorough empirical evaluation of their effectiveness in combination [Tseng et al. 2008; Truong 2016; Özyurt and Özyurt 2015; Essalmi et al. 2015]. Adaptation based on learning style and learner knowledge and their learning effectiveness in e-learning systems has been regarded as an important area of research because of the inherent complexity of adaptation, the large number of learning style models and dimensions, and the many variables that need to be controlled when evaluating the effectiveness of adaptation, such as prior experience and learner motivation [Brown et al. 2009; Akbulut and Cardak 2012; Mulwa et al. 2011; Gena 2005].

Although there have been numerous attempts to build and evaluate adaptive e-learning systems, there is a lack of carefully designed and controlled experimental evaluation of their learning effectiveness [Akbulut and Cardak 2012; Truong 2016; Özyurt and Özyurt 2015]. Research into learning style-based adaptation has led to a large number of small-scale and short-term applications of learning style models to small samples of learners [Chrysafiadi and Virvou 2013b; Brown et al. 2009; Truong 2016; Akbulut and Cardak 2012; Özyurt and Özyurt 2015]. The results of several studies concerning adaptation based on learning style are non-conclusive, limiting the confidence in generalising their learning effect [Alshammari et al. 2015a]. Another problem is the limited scope of experimental evaluation and the variables that are usually taken into account to determine the effectiveness of adaptation. Several important factors should be considered by taking into account both the pedagogical and usability factors when evaluating adaptive e-learning systems. Brusilovsky and Millán argue that a careful empirical evaluation of the effectiveness of adaptive e-learning systems is more important than proposing novel adaptive techniques with questionable benefits [Brusilovsky and Millán 2007].

With respect to the evaluation of adaptive e-learning systems, evaluation methodologies of human-computer interaction (HCI) have been broadly adopted [Gena 2005]. Among HCI evaluation methods, several researchers insist that experimental evaluation, also known as controlled experimentation, is the most appropriate approach for evaluating adaptive e-learning systems [Weibelzahl 2001; Gena 2005; Brown et al. 2009; Mulwa et al. 2011]. The case has been made that evaluation through experimentation with actual users is important for adaptive systems, as it produces evidence of the usefulness of adaptation [Weibelzahl 2001]. In general, experimental evaluation is concerned with the effectiveness and usability of a system by observation in controlled experiments [Höök 2000; Jameson 2009]; it plays a role in determining the advantages and effectiveness of adaptive systems, and in realistic situations with a fairly controlled approach [Gena and Weibelzahl 2007]. In addition, the appropriateness of this evaluation approach can be justified because the main source of information is usually generated from user-system interaction and users are the main targets of adaptive systems [Mulwa et al. 2011]. Experimental evaluation is chosen as the main method in this study for evaluating the effectiveness of different forms of adaptation, specifically through a number of experiments conducted to answer the research questions. Each experiment has specific objectives and hypotheses.

This research seeks to address the issue of whether the simple fact that adaptivity can be provided in e-learning systems to meet the characteristics of an individual learner – especially learning style and learner knowledge – means that adaptivity should in fact be provided. Are there aspects of learning style that were not investigated thoroughly that might lead to more effective learning, given the large number of existing learning style models? More thorough and carefully planned and conducted empirical evaluation of adaptive e-learning systems is needed; these issues are highly relevant to this work.

1.3 Research Questions

This study addresses four main research questions. These questions concern both the pedagogical and usability aspects of adaptation in e-learning systems. The investigation of the learning effectiveness and learner satisfaction of different forms of adaptation relates to the pedagogical aspect, while the usability aspect involves the investigation of the perceived usability level when providing adaptation.

Learning effectiveness is an essential factor that should be measured when evaluating adaptive e-learning systems [Brown et al. 2006; Paramythis et al. 2010]. Learner satisfaction also represents another important element in learning [Sun et al. 2008]; it is influenced by several affective factors such as motivation and engagement in the interaction, and relates to the extent to which learners believe the system they are interacting with meets their requirements [Shee and Wang 2008].

Another key issue is perceived usability, which relates to the ease of use and learnability of a specific system reflecting the extent to which users are satisfied with the interaction experience. It is expected that a high level of perceived usability when interacting with an e-learning system leads to more satisfied, engaged and motivated learners; this will reflect on their learning achievement [Ardito et al. 2006; Zaharias and Poylymenakou 2009].

The four research questions are as follows:

Research Question 1. Does adaptation based on the information perception dimension of learning style enhance learning and does it lead to a high level of learner satisfaction?

The effectiveness of adaptation based on learning style is investigated. More specifically, the information perception or sensory-intuitive dimension of the Felder-Silverman learning style model [Felder and Silverman 1988] was the basis of the implementation; it is recognised as one of the most important learning style dimensions [Felder and Brent 2005; Felder et al. 2002; McCaulley 1990]. It overlaps with and can be found in many different learning style models [Kolb 1984; Myers and McCaulley 1985; Felder and Silverman 1988]. It is correlated with several characteristics including learning styles, career skills and preferences and management styles [Felder and Silverman 1988; Feldman et al. 2014].

However, the information perception dimension of learning style has received scant attention in published research [Akbulut and Cardak 2012; Truong 2016; Özyurt and Özyurt 2015; Feldman et al. 2014]. These facts warrant a study that investigates both the provision of adaptation based on this particular dimension and the evaluation of its learning effectiveness [Alshammari et al. 2015c; Alshammari et al. 2015a].

Research Question 2. How do learning outcome and learner satisfaction vary if an adaptive e-learning system is based on the following learner characteristics:

- The information perception dimension of learning style alone;
- Knowledge level alone;
- A combination of the two characteristics?

Some researchers argue that there are few studies that carefully examine the effect of combining two or more learner characteristics or sources in an adaptive e-learning system [Tseng et al. 2008; Essalmi et al. 2010; Truong 2016]. In particular, learner knowledge is considered one of the important learner characteristics to take into account in adaptive e-learning systems [Brusilovsky and Millán 2007; Papanikolaou et al. 2003; Klasnja-Milicevic et al. 2011]. Furthermore, the major learning theories – whether behaviourist, cognitivist or constructivist in outlook – emphasise the importance of learner knowledge level when planning and delivering instruction [Ertmer and Newby 1993; Snow 1977]. A combination of learning style and learner knowledge are also used as a basis to provide adaptation. An investigation of the learning effectiveness and learner satisfaction when providing adaptation based on each characteristic and in combination are also taken into account.

Research Question 3. Do adaptive e-learning systems based on the information perception dimension of learning style and knowledge level yield higher levels of perceived usability than non-adaptive systems?

Research Question 4. Is there a relationship between perceived usability levels and learning outcomes in adaptive e-learning systems and non-adaptive systems?

Perceived usability remains an issue that requires investigation [Tsandilas and Schraefel 2004; Höök 1998]. When a system is not sufficiently usable, learners may become frustrated and focus on the e-learning system rather than on the learning content [Ardito et al. 2006]. An adaptive e-learning system can be usable in terms of its usage but not in terms of the underlying pedagogical perspective and vice versa [Gena 2005; Höök 2000]. This issue may therefore lead to less effective and less efficient learner-system interaction [Orfanou et al. 2015]. Ardito et al. point out the need for a better understanding of where adaptation in e-learning systems is beneficial and where it is harmful [Ardito et al. 2006]. Zaharias and Poylymenakou also state that "very little has been done to critically examine the usability of e-learning applications" [Zaharias and Poylymenakou 2009]. The perceived level of usability and the relationship between usability and learning outcome when providing adaptation are also investigated in this work [Alshammari et al. 2015b; Alshammari et al. 2016].

1.4 Research Methodology

Since the scope of this research relates mainly to adaptive e-learning systems, the work began by analysing the previous literature to identify and classify major learning theories and the concept of learning style. Then, an investigation of the issues related to adaptation based on learning style and learner knowledge in e-learning systems was carried out including an investigation of usability issues of adaptive e-learning systems and how they are evaluated. The research identified issues which require further study.

A design of a conceptual adaptive framework which draws on past models and frameworks in published research was initially proposed. As an instantiation of that framework, different forms of adaptation based on learning style and learner knowledge are implemented in an adaptive e-learning system. The main goals of developing the system are to:

- validate the proposed framework by taking into account its different components such as the domain model, learner model and adaptation model;
- evaluate the proposed approach of learning style adaptivity by focusing on the information perception dimension of learning style;
- evaluate the learning effectiveness and learner satisfaction and how they differ when providing adaptation based on the information perception dimension of learning style

alone, knowledge level alone and adaptation based on the combination of learning style and knowledge level;

- evaluate the perceived level of usability and its relationship with learning outcome;
- validate the ability of the system to accommodate different learner characteristics.

After reviewing relevant theories and research, identifying the main research questions and designing an adaptive e-learning system, the schematic process for each experiment was to develop research hypotheses, identify experimental variables, data collection tools and experimental procedures, select participants, conduct the experiment, collect and analyse data and draw conclusions regarding the research hypotheses [Keppel 1991; Chin 2001].

To improve the execution of the experiments, a pilot test was conducted prior to each experiment with three to four participants. The main objectives of the pilot tests were to check the randomisation process of participants in the experiment's conditions, technical issues related to the developed system, data collection reliability and consistency, the difficulty level of learning material, experiment duration and issues such as confusion and participant questions.

1.5 Research Contribution

Several important contributions to knowledge in the field of adaptive e-learning systems are made by the research reported in this thesis.

One contribution relates to the review of adaptive e-learning systems taking into account their main components including the domain model, the learner model and the adaptation model; three fundamental components necessary for any adaptive e-learning system in order to provide adaptation [Alshammari et al. 2014]. In addition, usability issues of these systems and how they are evaluated are also covered in the review.

Another contribution relates to the proposed adaptive e-learning framework; it can be used as a reference model to design instances of adaptive e-learning systems by focussing on different perspectives of the domain model, the learner model and the adaptation model. Within the overall framework, an adaptive e-learning system has been designed and implemented. The system has been essentially developed as a means to execute a set of experiments in order to validate the proposed framework and to evaluate the effectiveness of different forms of adaptation. The learner model of the system incorporates two learner characteristics: the information perception dimension of learning style and the knowledge level. The system can be configured to provide adaptation based on the information perception dimension of learning style alone, knowledge level alone and a combination of the two characteristics. In addition, computer security is used to demonstrate one particular domain of the system. Computer security has rarely been the domain of adaptive e-learning systems; the work in this thesis, thus, also offers some contribution to computer security education [Alshammari et al. 2015d].

The major contribution of this work comes from the careful design and execution of the experiments, and from the thorough analysis and reporting of the quantitative findings of three experiments with a focus on the pedagogical and usability aspects when providing different forms of adaptation. The three factors of learning effectiveness, learner satisfaction and perceived usability are taken into account when evaluating adaptation. The results of the experiments can offer more evidence for the importance of personalisation and adaptation of learning material and their sequencing to meet the different needs of different learners in e-learning systems.

The three experiments carried out to address the research questions are summarised as follows.

- Experiment 1 was conducted to investigate adaptation based on the information perception dimension of learning style and its effect on learning outcome and learner satisfaction.
- Experiment 2 was carried out to explore the effects of three classes of adaptation and how they vary in terms of learning outcome and learner satisfaction. The first is based on the information perception dimension of learning style alone, the second is based on knowledge level alone while the third caters to the combination of the two characteristics.
- Experiment 3 was undertaken to evaluate the perceived usability level, using a standard usability measure, and to investigate the relationship between perceived usability and learning outcome.

1.6 List of Publications

A number of research papers which resulted from this work were accepted and published in international conferences. These papers are listed below:

- **M. Alshammari**, R. Anane, R. Hendley. An Empirical Evaluation of Adaptation based on Learning Style and Knowledge level. The 13th International Conference on Intelligent Tutoring Systems (ITS-2016), Zagreb, Croatia, [Accepted].
- **M. Alshammari**, R. Anane, R. Hendley. Usability and Effectiveness Evaluation of Adaptivity in E-Learning Systems. The 34th Annual ACM Conference on Human Factors in Computing Systems (CHI-2016), San Jose, USA, pp2984-2991.
- **M. Alshammari**, R. Anane, R. Hendley. Design and Usability Evaluation of Adaptive E-learning Systems based on Learner Knowledge and Learning Style. Human-Computer Interaction–INTERACT 2015, Bamberg, Germany, pp584-591.

- **M. Alshammari**, R. Anane, R. Hendley. The Impact of Learning Style Adaptivity in Teaching Computer Security. The 20th ACM conference on Innovation and technology in computer science education (ITiCSE-2015), Vilnius, Lithuania, pp135-140.
- **M. Alshammari**, R. Anane, R. Hendley. Students' Satisfaction in Learning Style-Based Adaptation. The 15th IEEE International Conference on Advanced Learning Technologies (ICALT-2015), Hualien, Taiwan, pp55-57.
- **M. Alshammari**, R. Anane, R. Hendley. An E-Learning Investigation into Learning Style Adaptivity. The 48th Hawaii International Conference on System Sciences (HICSS-48), January 5-8, 2015, Hawaii, USA, pp11-20.
- **M. Alshammari**, R. Anane, R. Hendley. Adaptivity in E-Learning Systems. The 8th IEEE International Conference on Complex, Intelligent, and Software Intensive Systems (CISIS 2014), Birmingham, UK, pp79-86.

1.7 Thesis Structure

This thesis is comprised of six chapters including this introduction. Chapter 2 presents the theoretical foundations of learning and outlines several key learning theories. A discussion of these theories and their implications for instruction is included to identify how people learn. In addition, because learners differ in their approaches to learning, the concept of learning style is explored, as it is highly relevant to learning and is central to the present study.

Chapter 3 discuses technology-enhanced learning, also known as e-learning. It begins by outlining the earliest uses of distance learning technology. It also defines e-learning, covering different terminologies, discussing the theoretical implications for e-learning and analysing current e-learning systems, including an analysis of their merits and limitations. The chapter then presents the main concepts of adaptivity in e-learning systems, which is viewed as a solution to some of the drawbacks and limitations of traditional e-learning approaches. The chapter also reviews some existing adaptive e-learning frameworks and systems and investigates how they are evaluated. Usability issues and challenges in adaptive systems are also covered, with research issues highlighted.

Chapter 4 provides an adaptive e-learning framework. It incorporates the major components of analogous systems including the domain model, the learner model and the adaptation model. Within the overall framework, the chapter also describes the design and development of an adaptive e-learning system. The main aims of the system are to validate the proposed framework and to evaluate the effectiveness of different forms of adaptation. The system provides adaptation that takes into account two primary learner characteristics: learning style and learner knowledge. The rationale for choosing these two characteristics is also presented.

Chapter 5 evaluates the effectiveness of different forms of adaptation generated by the adaptive e-learning system. It begins by outlining the evaluation method, including dependent and independent variables, data collection tools and data analysis. Three experiments are presented and discussed, each with its own specific objectives and hypotheses. Experiment 1 is concerned with the effectiveness of learning style adaptivity, Experiment 2 examines the effectiveness of adaptation based on the combination of learning style and learner knowledge and Experiment 3 investigates the perceived usability and its relationship to learning outcome.

Finally, Chapter 6 concludes the thesis by summarising the work, revisiting the research questions and highlighting and reflecting upon the main contributions of this research. The chapter also highlights the limitations of this study and points to possible future research avenues.

Chapter 2. Learning Background

2.1 Introduction

This chapter presents the theoretical foundations of learning. It identifies different approaches to learning and outlines several key learning theories. A discussion of these theories and their implications in instruction is also included. As learners differ in their approaches to learning, the concept of learning style is also covered; this concept is highly relevant both to learning itself and to this research.

2.2 Learning Theories

2.2.1 Introduction

Learning has been defined in several ways by learning psychologists and educational theorists, and it is a challenge to formulate a universally agreed definition [Ormrod 2012]. However, many definitions of learning have certain elements in common. A definition that integrates the main conceptual approaches to learning is the following: "Learning is an enduring change in behavior, or in the capacity to behave in a given fashion, which results from practice or other forms of experience" [Schunk 1991]. Three features of learning can be elicited from this definition: it involves a change, persists over time and occurs as a result of experience. Learning can also be defined as a process of gaining, acquiring and modifying knowledge, attitudes, skills or behaviours [Bransford et al. 2000; Schunk 1991; Ertmer and Newby 1993]. However, the idea that learning is permanent is debatable, and some researchers have claimed that learning can be forgotten [Anderson 2000].

Learning depends on many factors, including the content to be learned or taught, the context or environment in which learning occurs, the characteristics and knowledge level of learners and the learning facilitators and teachers [Anderson 2008]. Other important learning factors include motivation, engagement and the affective state of learners [Keller 1987]. Motivation can be defined as an internal state that arouses people to act or behave in a particular way, and it keeps them engaged in certain activities [Ormrod 2012]. Motivation can be reflected in cognitive, emotional and behavioural engagement in certain activities; it increases time spent on a learning task, an important factor that affects learning outcome [Fredricks et al. 2004]. Another factor related to motivation is affect concerning learners' feelings, emotion, sentiments and moods [O'Regan 2003]. Affect influences learning as stated by Ormrod that "people can typically store and retrieve information with emotional overtones more easily than they can recall relatively nonemotional information" [Ormrod 2012].

Learning normally occurs when knowledge is gained by the learner [Jonassen 1991]. However, there are two opposing views of how knowledge is gained. These two views – empiricism and rationalism – have existed for centuries and have influenced current learning theories [Hofer and Pintrich 1997]. The view of *empiricism* is that experience is the main source of knowledge and that knowledge is gained as a result of interactions with the learning environment mainly through sensory channels such as ears, eyes and hands [Schunk 1991]. The view of *rationalism* is that knowledge is derived from reasoning and information retrieval and arises through the mind without the aid of the senses [Ertmer and Newby 1993; Schunk 1991].

The complexity of learning has led to the development of three fundamental classes of learning theory or schools: behaviourism, cognitivism and constructivism [Ertmer and Newby 1993]. Although there may exist some overlap between these theories, they differ in their conceptualisation and description of learning [Schunk 1991]. Behaviourism, cognitivism and constructivism are described in the following sections because of their importance in describing and understanding learning and because of their relevance to this research.

2.2.2 Behaviourism

Behaviourism is primarily concerned with human behaviour and ignores the processes performed by the human mind [Bechtel and Graham 1998]. Learning is expected to occur when an appropriate response is made to a given environmental stimulus [Skinner 2014]. The stimulus can be illustrated by a learner being presented with a mathematical equation to solve (e.g., 4+3); the learner's answer (i.e., 7) is the response. The primary concern in behaviourism is to understand the association between the stimulus and response, and how it can be strengthened and maintained [Winn 1990]. The reward or punishment for a new behaviour represents one of the key principles of this theory. According to behaviourism, if a reward is given to a learner for a particular behaviour, it will encourage the learner to repeat the same behaviour in similar situations. In contrast, if a punishment is given, the learner will be less likely to behave in the same way.

Behaviourist theories assume, however, that the learner is a passive recipient of knowledge and that it is the expert's or teacher's responsibility to efficiently and effectively transfer knowledge [Mayer 2009]. Environmental factors in learning receive the greatest emphasis, with less focus on other factors, including the learners themselves. The existing knowledge of learners can be evaluated in order to determine the starting point of instruction, but the planning and organisation of stimuli and responses, within the learning environment, represent the critical factors [Mayer 2009; Gao 2003]. Learning content should be arranged in a predefined order, and teachers should use cues (i.e., to initially stimulate the appropriate learner's response) and reinforcement (i.e., to strengthen correct responses to the target stimulus) [Winn 1990]. These strategies may be effective for recalling, illustrating and applying knowledge. However, language development and the acquisition of high-level skills such as problem solving and critical thinking are not well explained by behaviourist theories [Schunk 1991].

2.2.3 Cognitivism

Cognitive science has prompted learning theorists to de-emphasise some ideas of behaviourism and stress more complex cognitive processes such as problem solving, language development and critical thinking [West et al. 1991]. In contrast to behaviourist approaches to learning, cognitivist theories emphasise the acquisition of knowledge and the learner's mental processes [Ertmer and Newby 1993; Stepich and Newby 1988; Schunk 1991]. The metaphor of the mind as a computer can be used to describe cognitivist theories: there is an input (information), process and output. Cognitivist theories focus on the way information is received, structured, stored and retrieved by the human mind. Behaviour – *what learners do* – does not represent a main concern of cognitivist theories; they address mainly *what* knowing is and *how* it occurs [Jonassen 1991].

However, both cognitivism and behaviourism emphasise the importance of environmental factors in enhancing learning, and they both view instructional approaches such as explanation, illustration and demonstration as helpful guides for learning. They also share the view that learning is situated in the context of experimentation, practice and the provision of appropriate feedback [West et al. 1991]. Cognitivist and behaviourist approaches may not differ in the way they distinguish the factors that influence learning [Schunk 1991]. Cognitivist theories view the learner as having an active role in the learning process and assume that the learner engages in mental activities such as coding, transforming, storing and retrieving information, which can lead to an appropriate response [Winn 1990]. According to cognitivist theories, understanding or knowledge transfer can be confirmed when a learner successfully stores and retrieves information and acquires the ability to apply knowledge in different contexts [Schunk 1991]. Prior knowledge is also important and should be assessed to establish the ways in which new information can be assimilated into the learner's mind [Ertmer and Newby 1993].

Cognitivist theories provide explanations of more complex forms of learning such as reasoning, problem solving, critical thinking and information processing [Schunk 1991]. It is important to note that both cognitivist and behaviourist theories have the same goal with respect to instruction: to transfer knowledge to learners as efficiently and as effectively as possible [Bednar et al. 1992]. They both emphasise the view that knowledge can be analysed and decomposed into simple chunks. The use of feedback is central for both behaviourists and cognitivists, but for different reasons. Behaviourists use feedback to adjust behaviour in the desired direction, whereas cognitivists aim to support accurate mental connections [Ausubel et al. 1968]. Moreover, behaviourists focus on the design of the learning environment, whereas cognitivists seek processing strategies that optimise knowledge transfer [Ertmer and Newby 1993].

Cognitivist theories offer teachers a number of insights into instruction [Stepich and Newby 1988]. Teachers should understand that learning outcomes may be affected by different learners' experiences. Learners' prior knowledge, abilities and experiences should also be taken into account when organising and structuring new knowledge for optimal learning. Active experimentation and practice during learning supported by appropriate feedback to learners when needed are also important.

2.2.4 Constructivism

The assumptions of behaviourism and cognitivism are primarily objectivistic; that is, they assume the world is real and external to the learner. According to these theories, mapping the world structure onto the learner is the main goal of instruction [Jonassen 1991]. Some cognitivists have questioned these objectivistic assumptions and adopted a more constructivist approach to learning and understanding [Bruner 1966]. Constructivism is considered an extension or part of cognitivism, but it has a specific focus. It emphasises the experience resulting from the learner's interactions with the learning environment, and it conceptualises the learner's mind as a processor responsible for reasoning, information retrieval and reflection [Schunk 1991; Ertmer and Newby 1993]. Constructivists do not believe knowledge is mind-independent and can be simply mapped onto the learner, as is claimed by cognitivists and behaviourists. Although constructivists do not reject the existence of the external world, they argue that learners create meanings from their interactions with the world and have their own interpretations of their experiences [Bruner 1966].

Both the learning environment and the learner are vital in constructivist approaches. Each interaction between learner and learning environment creates knowledge against the background of the entire history of previous interactions [Knowles 1980]. This suggests that knowledge is linked to both the learning context and the learner's prior experiences. The learner is assumed to have a very active role and participation in learning who can construct knowledge by elaborating, integrating and synthesising information rather than passively receiving knowledge from the teacher or expert [Jonassen 1991]. The responsibility of a teacher is not to transfer knowledge by lecturing or explaining learning content, but to facilitate the learning process and to organise it into several formats to meet the diverse requirements of learners, such as their prior knowledge and learning abilities [Ertmer and

Newby 1993]. In addition, constructivism calls for learner-centric instructional approaches, which support self-directed, self-paced and relatively independent learning as well as immediate application of knowledge [Moore 1989].

Constructivism, however, lacks a concept of structured learning, a limitation that can be, on the one hand, challenging to novice learners who prefer well-organised learning environments and, on the other hand, beneficial to advanced learners who thrive in less structured domains [Jonassen 1991]. Furthermore, learner control, which is emphasised by constructivists, may not always be a productive approach; learners sometimes need to be directed by teachers in order to connect new knowledge to what they already know. Without teacher guidance, learners may develop misconceptions about what they are learning. This may lead some learners to be confused and frustrated about their learning processes. Learners should be provided with a variety of content presentations [Ertmer and Newby 1993]. Knowledge acquisition should be adaptive, taking into account three critical learning factors: concrete experience, abstract concepts and learning environment [Brown et al. 1989].

2.2.5 Summary

It may be the case that learners gain different competencies depending on whether they are exposed to behaviourist, cognitivist or constructivist instructional approaches. This leads to the question as to which learning models are the most effective. Given the complexity of learning, the answer may be dependent mainly on the learning context. In addition, what works for novice learners may not work for advanced learners. Similarly, concepts or problem-solving lessons are not taught in the same way as are facts or examples.

It is critical to provide an appropriate match between learner, content and instructional strategies (i.e., the way that content is delivered to the learner) [Ertmer and Newby 1993;

Schunk 1991; Moore 1989; Bransford et al. 2000]. Behaviourist theories may be beneficial when planning content and instructional strategies such as stating learning objectives and providing immediate feedback. Cognitivist theories may be similarly beneficial in their emphasis of appropriate feedback [Ausubel et al. 1968]. However, behaviourist theories neglect the learner's mind and treat all learners in the same way [Bechtel and Graham 1998]. In contrast, cognitivist theories emphasise that the learner's mind as an important factor in learning [Stepich and Newby 1988]. More complex forms of learning such as problem solving and critical thinking are also supported by cognitivist theories [Schunk 1991]. Constructivists argue that knowledge is constructed by learners during their interactions with the learning environment [Bruner 1966; Ertmer and Newby 1993]. They also believe that each learner has a unique learning process [Jonassen 1991; Brown et al. 1989]. Constructivism also calls for multiple content presentations for each topic in order to enhance learning [Ertmer and Newby 1993; Schunk 1991].

The behaviourist approach may effectively support the mastery of content (*knowing what*); the cognitivist approach may more usefully support more complex forms of learning such as problem solving and critical thinking (*knowing how*); and the constructivist approach may be more suitable for dealing with ill-defined domains through information elaboration and reflection and may better support different learner needs. Prior knowledge and learning tasks should be considered when selecting a specific approach. It is crucial to carefully consider learners' competence levels and the context of the task when selecting instructional strategies. Nevertheless, according to Ertmer and Newby, "Powerful frameworks for instruction have been developed by designers inspired by each of these perspectives. In fact, successful instructional practices have features that are supported by virtually all three perspective (e.g., active participation and interaction, practice and feedback)" [Ertmer and Newby 1993].

2.3 Learning Style

2.3.1 Introduction

According to the cognitivist and constructivist theories of learning, several learning strategies should be integrated to accommodate individual differences and learning style [Cassidy 2004]. For example, different modes of information like visual, verbal and textual may be taken into account to support learning [Clark and Paivio 1991]. Hence, the concept of learning style represents one of the most important issues in learning [Keefe 1979; Dunn and Griggs 2003; Honey and Mumford 1989]. It has been argued that if a learner has a strong affinity for a particular learning style, the learning material and strategies should match this style to enhance learning [Felder and Silverman 1988]. In addition, Coffield et al. stated that “There is a strong intuitive appeal in the idea that teachers and course designers should pay closer attention to students’ learning styles” [Coffield et al. 2004].

Keefe defines learning style as a composition of affective and cognitivist factors that specify the way in which a learner perceives and interacts with a learning environment [Keefe 1979]. According to Honey and Mumford, learning style comprises the observed behaviours and attitudes that indicate an individual’s preferred way of learning [Honey and Mumford 1989]. Researchers typically use the terms ‘learning style’ and ‘cognitive style’ interchangeably, although cognitive style may represent a specific aspect of learning style [Cassidy 2004]. Other commonly used terminology associated with learning style includes ‘learning preferences’, ‘learning skills’, ‘learning strategy’ and ‘approaches to studying/learning’ [Coffield et al. 2004]. Different interpretations and terminologies have led to the development of many learning style models and frameworks.

2.3.2 Types of Learning Style

In view of the different terminology related to learning style, and given the existence of a large number of learning models [Coffield et al. 2004], a categorisation of these models can illuminate their key aspects. The model of Curry's onion can be used to classify learning theories [Curry 1983]. It uses the metaphor of an onion, as shown in Figure 1, which has three primary layers; each learning style corresponds to a particular layer. The main classification criterion in the onion model is the degree of stability over time of the preferences represented by each layer.

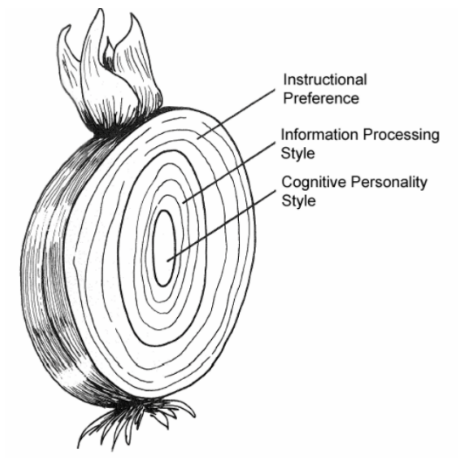


Figure 1. Curry's onion model of learning style theories, taken from [Wolf 2007].

In Curry's model, the outermost layer of the onion represents instructional preference. It is concerned with various modes of information delivery and may change frequently; instructional preference is assumed to be the least stable over time [Curry 2000]. The middle layer represents information processing styles. They are concerned with the way the brain processes information, which can influence the way learners remember, think and elaborate on information. Information processing styles have greater stability over time than instructional preference. The innermost (core) layer of the onion represents cognitive personality styles; these styles are based on personality traits that have an indirect impact on the way learners interact with the learning environment. Cognitive personality styles are believed to be the most stable over time [Curry 1983; Curry 2000].

Coffield et al. criticise the theoretical foundation of Curry's onion model because it uses psychoanalytic assumptions rather than quantitative evidence to determine learning style stability. Based on several learning style overviews and on quantitative evidence, they classify learning style models according to 'families of learning styles' [Coffield et al. 2004]. The model suggests that there are *five* families of learning styles as follows.

- **Constitutionally based learning styles and preferences.** These styles are largely constitutionally based including the four sensory modalities: visual, auditory, kinaesthetic and tactile. Learning styles belonging to this family are assumed to be fixed and very difficult to change.
- **Cognitive structure.** Learning styles reflect structural characteristics of the cognitive system that are embedded in personality construction. The styles belonging to this family are assumed to be generalised habits of thought (i.e., an enduring structural basis for such behaviour).
- **Stable personality types.** Learning styles are viewed as embedded characteristics within the personality traits which are assumed to shape all aspects of an individual's interaction with the environment. These styles and preferences are mostly stable but can change over time.
- **'Flexibly stable' learning preferences.** Learning styles are viewed as flexibly stable learning preferences. Although, the preferences can change slightly from one situation to another, there is some long-term stability of learning styles.
- **Learning approaches and strategies.** Moving on from learning styles to a holistic and active view of approaches to learning, study strategies, orientations and conceptions of

learning. These approaches and strategies need to be adapted to match the learning context so that they are frequently changed depending on the situation.

This classification may provide general insights into the concept of learning style. However, some dimensions of learning style appear across different learning style models, and these models may be classified according to different layers, groups or categories.

2.3.3 Learning Style Models

As mentioned above, a large number of learning style models have been developed [Coffield et al. 2004; Felder and Silverman 1988]. Although it is beyond the scope of this work to review and provide substantial descriptions of all these models, a number of learning style models will be selected and reviewed based on their theoretical importance in the field, and the degree to which they are used. The selection process takes into account the *five families of learning styles* described in the previous section [Coffield et al. 2004]. Table 1 presents some learning style models as examples of each learning style family. Each model will be discussed in this section.

Table 1. Summary of learning style models.

	Family of learning style	Learning style model
1	Constitutionally based learning styles and preferences	Dunn and Dunn
2	Cognitive structure	Witkin
3	Stable personality types	Myers-Briggs
4	'Flexibly stable' learning preferences	Kolb Honey and Mumford Felder and Silverman
5	Learning approaches and strategies	Entwistle

2.3.3.1 The Dunn and Dunn Model

Originally developed in 1974, the Dunn and Dunn model has been improved and extended over the years [Dunn and Dunn 1974]. It comprises five major categories, each of which contains several factors. The *environmental* category includes sound, temperature, light and seating/furniture design. The *emotional* category is concerned with motivation, task persistence and responsibility. The *sociological* category deals with preferences for learning alone, in a pair, in a small group or as part of a team. The *psychological* category refers to right/left, global/analytic and impulsive/reflective preferences. The *physical* category contains factors related to perception/modality preferences (visual, verbal), food and drink intake, time of day and mobility.

Dunn and Dunn claim that these traits are fixed preferences and cannot be changed [Dunn and Dunn 1974]. As the theoretical basis of the model assumes simplistic connections between physiological and psychological preferences and brain activity, this claim is questionable. This model has not been available to other researchers – other than those who developed the model – in order to confirm its applicability, reliability and validity [Brown 2007]. Some researchers also argue that this model is not based on robust empirical work [Coffield et al. 2004]. Furthermore, there are different versions of the model for children of different ages, as well as a version for adults. The learning style assessment used is a questionnaire containing over 100 items. Responding to this lengthy questionnaire may become frustrating and tedious.

2.3.3.2 The Witkin Model

This is a cognitive-style model concerned with the way learners perceive, structure and recall information. It categorises learners as field dependent (FD) or field independent (FI) based on Witkin's work in the 1960s [Witkin et al. 1962]. FD learners tend to have a global perspective and may find it difficult to separate minor details from the big picture or the overall viewpoint. FI learners are very analytical and can concentrate on minor or specific details irrespective of the learning environment.

The cognitive style of learners (FD or FI) can be identified by using the Group Embedded Figures Test; it contains 25 items, and is a reliable and validated tool [Witkin 1971].

However, some researchers argue that the model assesses learning ability rather than learning style [Messick 1984].

2.3.3.3 The Myers-Briggs Type Indicator

The Myers-Briggs Type Indicator (MBTI) is used to identify individuals' personality types according to Jung's psychodynamic type theory [McCaulley 1990]. The main assumptions of this theory are that experiences and future expectations influence an individual's personality and that personality is extremely sensitive to the external world [Myers and McCaulley 1985]. The MBTI has four dimensions, and each dimension contains a pair of opposite preferences called dichotomies, resulting in 16 possible combined types:

- Extroversion – Introversion: it relates to the attention focus of a person
- Sensing – Intuition: it deals with the way information is perceived by a person
- Thinking– Feeling: it focuses on the way decisions are taken by a person
- Judging – Perceiving: it describes the way of dealing with the external world by a person

Extroverts tend to try things out and focus on the external social world; introverts think about things and focus on the internal world of ideas. Sensors focus on facts and procedures and prefer practical applications; intuitors are imaginative and focus on meanings, relationships and possibilities. Thinkers tend to make logical decisions based on predefined rules; feelers take into account personal and humanistic factors to make decisions. Judgers tend to follow organised schedules and agendas, and they focus more on outcomes than on processes of creation; perceivers tend to be open, flexible and adaptive to changing circumstances, and they enjoy processes more than outcomes.

The MBTI standard assessment instrument has 93 items [Quenk 2009]. Another version contains 126 items, only 95 of which are used for personality type scoring calculations [Myers and McCaulley 1985]. It has been applied in education to assess characteristics such as learning style and learner interactions [Harrington and Loffredo 2010]. Despite the MBTI's usefulness in learning, responding to a lengthy instrument is challenging, and the MBTI suffers from several reliability and validity issues [Coffield et al. 2004].

2.3.3.4 The Entwistle Model

According to Entwistle, the main factors that lead to and are affected by learners' typical approaches to learning include learners' conceptions of and orientations to learning, types of knowledge and differing motives [Entwistle et al. 1979]. These factors usually fluctuate over time and take form on a task-to-task basis [Coffield et al. 2004]. Entwistle's model distinguishes between three learning approaches: deep learning, surface learning and strategic learning [Entwistle et al. 2001]. Learners applying a *deep learning approach* interact actively and logically with learning content and seek to gain a broad view of the subject. They match ideas to previous knowledge and experiences by looking for patterns and underlying concepts.

In contrast, learners who take a *surface learning approach* do not intentionally become interested in and seek to understand a subject. They aim merely at meeting the requirements of the course and see its content as unrelated bits of knowledge. They usually focus narrowly on details, and especially on the details of the course that are more likely to be assessed. In the *strategic learning approach*, learners combine both deep and surface learning approaches in order to understand the subject and achieve remarkable outcomes in terms of course marks. Learners who adopt the strategic approach manage their time and effort in order to study effectively and consistently. They evaluate the effectiveness of different ways of studying and identify the right learning conditions and material. They are also aware of the course requirements and the way coursework is assessed.

Several instruments have been developed to measure learning approaches, such as the Approaches to Studying Inventory [Ramsden and Entwistle 1981] and the Approaches and

Study Skills Inventory for Students [Entwistle et al. 2000]. However, many of the subscales of these inventories have low reliability, and their test-retest reliability has not been reported [Coffield et al. 2004].

2.3.3.5 The Kolb Model

The learning style model proposed by Kolb, who is an influential figure in the learning style field, is based on the experiential learning theory; learning is conceived as a cyclical process, as shown in Figure 2 [Kolb 1984]. This theory emphasises four abilities of learners that support effective learning: concrete experience, reflective observation, abstract conceptualisation and active participation.

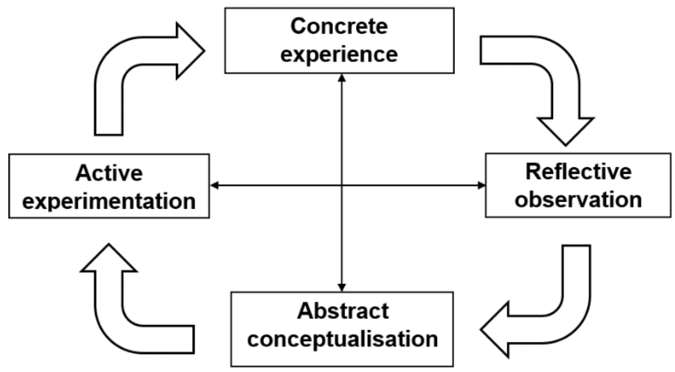


Figure 2. Kolb's experiential learning cycle.

Concerning the description of these abilities, an individual should be able to carry out a specific action and then observe the results of the action in a particular situation or context (concrete experience). The ability to review and reflect upon what has been done and experienced without task involvement is important (reflective observation). The learner should also be able to interpret the learning events that have been observed and to understand the relationships between the events' factors (abstract conceptualisation). The fourth ability is concerned with the application of what is known in a new context or situation (active participation).

Kolb developed a learning style inventory to put the experiential learning theory into practice [Kolb 2005]. A learner is placed at the intersection between the vertical line connecting concrete experience and abstract conceptualisation and the horizontal line connecting active participation and reflective observation (see Figure 2). There are four types of learners:

- Converger (abstract/active): Learners with a converging style may perform better in problem-solving tasks, decision making, and generating practical applications from ideas.
- Accommodator (concrete/active): Learners grasp knowledge through concrete experience and transform their knowledge into active experimentation. They are good at problem-solving activities, but they may be seen as overly proactive and impatient.
- Diverger (concrete/reflective): Learners are imaginative and able to generate ideas from different perspectives. They are people-oriented and adapt by observation.
- Assimilator (abstract/reflective): Learners have strong abilities to create theoretical and mathematical models and are concerned with logic and abstract concepts rather than interacting with people. They focus on abstract conceptualisation and reflective observation.

Kolb's model may be criticised for assuming that learning always occurs in linear and ordered steps and for failing to integrate social and cultural aspects of learning [Konak et al. 2014]. In addition, its related instrument (the Inventory of Learning Style) for identifying individuals' learning styles has been subject to reliability and validity issues [De Ciantis and Kirton 1996].

2.3.3.6 The Honey and Mumford Model

Honey and Mumford's model is very similar to the Kolb's learning style model [Honey and Mumford 1989]. It also suggests four types of learners: activist (similar to accommodator), theorist (similar to assimilator), reflector (similar to diverger) and pragmatist (similar to converger). Activists learn by actively doing and trying something out. Theorists are logical thinkers and prefer to engage in the learning process via models, concepts and facts. Reflectors take an advantage of observation of what other people do from different perspectives and reflect on them before reaching a conclusion. Pragmatists prefer real-world examples and problem solving using standard procedures.

The Learning Style Questionnaire (LSQ), a self-report inventory for identifying individuals' learning styles based on the Honey and Mumford model, has been developed [Honey and Mumford 1989; Honey and Mumford 2006]. There are two versions of LSQ; one contains 80 questions, and the other has 40. Although there are some positive results regarding the model's internal consistency, there is a lack of evidence supporting its validity [Allinson and Hayes 1990]. In addition, the LSQ instrument is not free (i.e., a commercial product) and it is used mostly in management and human resources.

2.3.3.7 The Felder-Silverman Model

Felder and Silverman have developed a learning style model that takes into account major learning style models such as the Kolb model [Kolb 1984], the MBTI [Myers and McCaulley 1985] and the Dunn and Dunn model [Dunn and Dunn 1974]. The Felder-Silverman model contains four dimensions that can be viewed independently of each other [Graf et al. 2007]. Each dimension has two categories, as follows: information processing (active-reflective), input modality (visual-verbal), information understanding (sequential-global) and information perception (sensory-intuitive) [Felder and Silverman 1988].

The *information processing* dimension (active-reflective) is similar to the respective dimension in Kolb's model [Kolb 1984]. It involves the way learners process information. Active learners learn by trying something out and by interacting with peers; reflective learners learn by thinking deeply about the information independently before acting.

The *input modality* dimension (visual-verbal) deals with the preferred input mode and presentation of information. Visual learners may learn well with pictures, graphs and diagrams; verbal learners may grasp spoken and written information quickly.

The *information understanding* dimension (sequential-global) refers to the preferred way of structuring information. Sequential learners gain understanding by linear and logical steps and exhibit a strong interest in details; global learners learn on the basis of large and random leaps through sets of information and have a strong interest in overviews and broad knowledge.

The *information perception* dimension (sensory-intuitive) is related to the MBTI [Myers and McCaulley 1985] and also has similarities with the abstract-concrete dimension in Kolb's model [Kolb 1984]. This dimension concerns the most suitable type of information for individual learners. Sensory learners may benefit more from concrete information such as facts and examples; intuitive learners may perform better with abstract concepts such as theories and mathematical models. A combination of concrete and abstract learning material can also be provided to learners as appropriate; a concrete-to-abstract sequence of learning material can be provided for sensory learners whereas an abstract-to-concrete sequence can be more beneficial for intuitive learners.

The Felder-Silverman learning style model also identifies teaching styles that correspond to each dimension. It is concerned with instructional methods that support each component of the model. Table 2 describes the different dimensions of the Felder-Silverman model and the corresponding teaching style for each dimension. For example, sensory learners should be given concrete learning content, whereas intuitive learners should be provided with abstract material.

The Index of Learning Style (ILS[1]) was developed as an instrument for identifying individuals' learning styles according to the Felder-Silverman learning style model [Felder and Silverman 1988]. It contains 44 questions, with each dimension of the Felder-Silverman model having 11 questions. The ILS is considered a reliable and validated tool for identifying the learning style of learners [Felder and Spurlin 2005]. In addition, some studies have confirmed that there is acceptable evidence for independence, reliability and construct validity for each dimension of the Felder-Silverman model [Felder and Spurlin 2005; Graf et al. 2007; Zywno 2003].

Table 2. The Felder-Silverman learning and teaching style model.

Dimension	Category	Characteristics	Teaching style
Information processing	*Active*	Group work, asking questions, discussion, explanation, application, experimentation	Active learner participation
	Reflective	Independent work, thinking, theorising	Passive learner participation
Input modality	*Visual*	Pictures, diagrams, flow charts, video clips	Visual presentation
	Verbal	Text, formulas, audio clips	Verbal presentation
Information understanding	*Sequential*	Sequential steps, logical stepwise paths	Sequential perspective
	Global	Big picture, random steps	Global perspective
Information perception	*Sensory*	Facts, examples, practical orientation, patience with details	Concrete learning content
	Intuitive	Innovation, abstraction, new concepts, impatience with details	Abstract learning content

2.3.4 Issues in Learning Style

The idea of taking into account learning style in traditional learning by teachers and instructional designers seems to be intuitive [Coffield et al. 2004]. Learning style may be diagnosed in order to encourage learners to reflect on their learning style and to recognise

[1] http://www.engr.ncsu.edu/learningstyles/ilsweb.html [accessed online: December 2015]

their strengths and weaknesses, which in turn improves their self-awareness and metacognitive skills [Coffield et al. 2004]. Information about learning styles can also be used in the design of learning environments, the provision of instructional strategies and the selection of learning content. Furthermore, it has been argued that if a learner has a strong affinity with a particular learning style, the instructional material and strategies should match this style [Felder and Silverman 1988]. This may however be acceptable for short-term learning where the main aim is to make learning as easy as possible at the time of learning [Graf 2007]. In contrast, for long-term goals, it has been argued that learners should be trained according to their non-preferred learning styles [Kolb 1984; Messick 1984]. Nevertheless, it has been argued that a permanent teaching approach based on mismatched learning style is not recommended as it may harm learners [Gregorc and Ward 1977; Felder and Brent 2005].

In the field of learning style, however, little consensus has been reached on key topics [Coffield et al. 2004]. Although extensive research has been conducted, several important questions remain open and are under investigation and discussion. A large number of learning style models and theories have been developed, with each model or theory having different dimensions or components that emphasise different factors. There may also be some overlap between these models. In addition, appropriate syntheses and an identification of relationships between these models and their associated dimensions have not yet been fully explored [Cassidy 2004].

Another important issue relates to the method of measuring learning style which is often criticised. The learning style models are normally augmented with different instruments and tools for identifying learning style. The method typically used for identifying learning style is to ask learners about their preferences using self-report questionnaires. When using questionnaires for identifying learning style, different assumptions need to be taken into consideration such as motivation of learners and awareness of their learning preferences. The instruments and tools also differ widely in terms of their validity and reliability [Coffield et al. 2004; Graf et al. 2007].

Another issue is that theorists have made differing claims regarding the stability of learning styles. One claim is that learning styles are similar to instructional strategies; they are conceptualised as flexible and capable of change, because learning is viewed as situated and context specific [Pask 1976; Entwistle et al. 2001]. Some models, such as the Kolb model [Kolb 1984] and the Felder-Silverman model [Felder and Silverman 1988], characterise learning styles as ‘flexibly stable’. These models suggest that learning style is not a completely fixed trait but may be changed over time [De Ciantis and Kirton 1996]. Supporters of this view claim that it is still possible to create and rely on valid and reliable assessments that can be used for diagnostic and predictive purposes [Coffield et al. 2004]. Others argue that learning styles remain stable over a very long period of time or even that they are permanent traits and cannot be changed [Dunn et al. 1995].

In another concern, the field of learning style lacks substantial and hard empirical evidence in the claim that matching instructions according to learning style has a significant positive effect on learning outcome and learners’ achievement [Coffield et al. 2004]. Research into learning style has led to a large number of small-scale and short-term applications of particular models to small samples of learners [Pashler et al. 2008]. Furthermore, matching learning style with learning material and instructional strategies may be difficult in traditional learning (e.g., in classrooms or lectures). Teachers may not always have the time, resources and ability to assess the learning style of each learner and modify their teaching style accordingly [Pask 1976].

In contrast, in technology-enhanced learning, it is possible to accommodate different learning style models in order to provide more personalised learning. In this regard, many studies of learning style have been conducted, and they stress the importance of learning style in enhancing learning [Cassidy 2004; Akbulut and Cardak 2012; Truong 2016]. For example, Ford and Chen argue that matching the presentation of instructional material with learning style improves learning performance [Ford and Chen 2001]. A discussion of e-learning systems incorporating learning style is provided in Chapter 3 in more details.

It can be said that learners are simply different; they have different learning preferences and prefer particular types of content and specific instructional strategies. Learning style has the potential to improve learning when it is taken into account in instruction [Felder and Silverman 1988; Keefe 1979; Ford and Chen 2001; Cassidy 2004; Akbulut and Cardak 2012; Truong 2016]. The usefulness of the concept of learning style and its applications are still open to further investigation [Graf 2007; Coffield et al. 2004; Pashler et al. 2008]. Many researchers advocate carrying out high-quality and robust experimental evaluations considering all the confounding factors from which most learning style studies suffer [Akbulut and Cardak 2012; Pashler et al. 2008; Truong 2016; Coffield et al. 2004; Cassidy 2004; Özyurt and Özyurt 2015]. However, justifications for using a specific learning style model or dimension need to be explicit. Furthermore, it is necessary to use learning style assessment tools that have adequate reliability and validity.

2.4 Conclusion

This chapter has outlined several key concepts of behaviourist, cognitivist and constructivist learning theories. Although each theory has a distinct viewpoint about learning, there are some conceptual overlaps between them. Behaviourism is primarily concerned with the behaviour of the learner and neglects the mental processes performed by the learner's mind. Cognitivism focuses on the processes by which the learner's mind receives, organises, stores and retrieves information. Constructivism underlines the experience that results from the learner's interactions with the learning environment and the learning content. It also characterises the learner's mind as a processor that has the ability to reason, understand, recall and reflect. Behaviourist approaches may support the learner's understanding of content (*knowing what*). Cognitive approaches may be more beneficial in supporting complex modes of learning such as problem solving and critical thinking (*knowing how*). Constructivist approaches may be appropriate in dealing with ill-defined domains and may better support metacognitive and reflection skills. The careful selection of a learning approach or a combination of learning approaches is crucial.

This chapter has addressed learning styles, which is an important concern in learning. Consensus is lacking in the field of learning style, and a unified learning style model has yet to be developed. Learning style models have different dimensions, and each dimension has different categories. For example, the Felder-Silverman model has four dimensions, that is, active-reflective, visual-verbal, sequential-global and sensory-intuitive. The Kolb model has two main dimensions: concrete experience versus abstract conceptualisation and reflective observation versus active participation. There are some similarities between these models; for instance, the sensory-intuitive dimension in the Felder-Silverman model may be related to the concrete-abstract dimension in the Kolb model. Learning style models are usually augmented with a self-report questionnaire as an instrument for identifying individuals' learning styles. These tools vary in size, validity and reliability.

The stability of learning styles is also an important issue. Some learning styles are viewed as similar to instructional strategies; they are conceptualised as flexible and capable of change.

Other learning styles are viewed as ‘flexibly stable’ and not completely fixed traits but may be changed over time. Based on this view, it is still possible to create and rely on valid and reliable assessments that can be used for diagnostic and predictive purposes. In another view, learning styles are considered stable over a very long period of time or are even permanent traits and cannot be changed. Many educational theorists agree that taking learning style into account in instructions can improve learning. It has been argued that if a learner has a strong affinity with a particular learning style, the instructional material should match this style. However, justifications and a careful selection of a learning style model and its respective instrument should be taken into account.

Chapter 3. Adaptivity in E-Learning Systems

3.1 Introduction

The previous chapter discussed the theoretical foundations of learning in order to identify how people learn and how learning theories can be used to support learning. It also gave some background on the concept of learning style because of its importance as a learner characteristic, since people often learn, perceive and understand in different ways.

This chapter discuses technology-enhanced learning, also known as e-learning. It begins by briefly presenting the earliest uses of distance learning technology. It also defines e-learning, covering the different terminologies and discussing theoretical implications for e-learning, with highlights on current e-learning systems, including a discussion of their merits and limitations.

The chapter then presents the main concepts of adaptation in e-learning systems. Adaptivity is often considered as a solution to some of the drawbacks and limitations of traditional e-learning systems. The primary goal of adaptation is to enhance the learning process by meeting the different needs and preferences of individual learners. The chapter also reviews some adaptive e-learning systems and, in particular, investigates how their effectiveness has been evaluated. Usability issues and challenges in adaptive systems are also covered. Some research issues that should be addressed by further research are presented at the end of the chapter.

3.2 E-Learning

3.2.1 Introduction

One of the main features of modern online learning is the removal of distance barriers to education, which can now occur even though learners are spread across widely separated geographical areas. However, the concept of distance learning itself is not new and can be traced to at least the early eighteenth century, when Caleb Phillips placed an advertisement in the *Boston Gazette* in 1728, offering shorthand lessons delivered weekly by the postal system in the British colonies [Brown 2007]. Since then, educators have used the mail to deliver correspondence courses; this mode of learning was expanded in the twentieth century to include radio transmission, audio recordings and eventually television programmes. For example, there were about two hundred radio stations offering courses across the USA in the 1920s [Anderson 2008]. One of the first universities to offer television-based courses was the Western Reserve University in the 1950s while the Open University (OU), founded in the UK in 1969, created the foundation of modern British distance learning [Bower and Hardy 2004]. The OU used the latest forms of communication technology to offer entire degree courses via distance learning. The OU inspired similar programmes in higher education across the world, raising the scope and profile of distance learning [Bower and Hardy 2004].

As the number of personal computers and the intensity of their use have both increased over the last 25 years, they have been gradually integrated into educational settings. Initially used to teach typing using word-processing software, basic calculations, and creating and manipulating spreadsheets, educational software installed via CD and DVD was soon used in personal and networked computers to deliver a wide range of multimedia learning content. Both computers and software have evolved dramatically with the advancement of networking and the Internet, so that online learning is now a reality for learners and is becoming widespread at a global level. Distance learning, in which learners do not need to be physically present at a particular location, has made very successful use of the Internet as a method of communication. With the Internet revolution and the emergence of Web technology, new online learning environments have been created to support learning in both formal and informal contexts. For example, a recent addition to the range of distance learning options, first introduced in 2008 and emerging as a popular mode of learning in 2012, are Massive Open Online Courses (MOOCs) [Sinclair et al. 2015]. MOOCs attract millions of learners around the world to access courses offered by several universities via the Web. There are many commercial and non-profit providers of MOOCs including Coursera[2], Udacity[3], edX[4] and FutureLearn[5].

Online learning is also delivered by a wide variety of educational institutions to support formal learning for both their local and remote learners. The OU is still offering entire online courses that lead to certified degrees. Some individual universities offer online courses, such as the University of Liverpool[6], the University of Edinburgh[7] in the UK and the University of Illinois[8] in the USA. Recently, the Saudi Electronic University[9] which was founded in 2011 provides both postgraduate and undergraduate degree programmes along with life-long education through online courses.

With the growth of educational software in the 1990s, new terms have evolved that point to the different ways in which computers and software can be used to support learning.

[2] https://www.coursera.org/
[3] https://www.udacity.com
[4] https://www.edx.org/
[5] https://www.futurelearn.com/
[6] http://www.liv.ac.uk/
[7] http://www.ed.ac.uk/home
[8] http://www.online.uillinois.edu/
[9] https://www.seu.edu.sa/

Computer-based learning (CBL) is used when computers play a fundamental role as a component of the learning process [Ally 2004]. *Computer-based training* (CBT) is a related concept, focusing particularly on training to master a particular skill or proficiency in a workstation environment. CBT may include a tutorial explaining how to use a specific device or program or show practical procedures. Both CBL and CBT are broad concepts that effectively can refer to any type of computer use in an educational setting. C*omputer-assisted instruction*, or *computer-assisted learning*, describes contexts in which computers are used mainly as tools to support learning, providing the capacity for students to drill and practice, read tutorials and manipulate selected objects in simulation activities [Carbonell 1970].

Many applications have been developed to make online learning much easier to facilitate and more scalable. For example, a *virtual learning environment* (VLE) is a software system that helps tutors and teachers create and manage an online learning course with fewer technical skills to be accessed by their students in order to help them in learning [Watson and Watson 2007]. Additional features can also be integrated in VLEs such as forums, chat rooms, email and wikis. Another type of application is the *learning management system* (LMS), which is a "framework that handles all aspects of the learning process" [Watson and Watson 2007]. The scope of LMSs is wider than VLEs since a LMS may include features that are common to VLEs in addition to other features such administration, tracking, reporting and delivering learning programmes within an organisation. Other terms that are common in online learning include *computer-supported collaborative learning* and *computer-supported cooperative work*, both of which emphasise social interaction to facilitate learner-learner interaction and learner-teacher interaction to help expedite learning tasks that require group work [Magnisalis 2011].

3.2.2 E-Learning and Learning Theories

The previous section has made clear that an abundance of terms exist in distance and online learning. They are often used interchangeably and do overlap to a large extent, which makes it difficult to develop strict definitions and distinctions [Moore et al. 2011]. However, they all share the view that the learner is situated at a meaningful distance from the teacher and uses some form of technology – usually a computer – to access, share and interact with learning material, teachers or peers. The phrase ‘e-learning’ will be used throughout this thesis because of its popularity and ease of use.

There are many definitions of e-learning that reflect the different technologies and practices employed. Gardner and Holmes offer a simple view of e-learning as “online access to learning resources, anywhere and anytime” [Gardner and Holmes 2006]. Another outlook suggests that e-learning can be any learning material that is offered and can be accessed from a computer [Carliner 2004]. However, it has been argued that e-learning is not merely presenting and delivering learning material using computers, but must focus on both the learner and the learning process [Ally 2004]. E-learning can be generally defined as “the use of the Internet to access learning materials; to interact with the content, instructor, and other learners; and to obtain support during the learning process, in order to acquire knowledge, to construct personal meaning, and to grow from the learning experience” [Ally 2004].

A number of learning theories have been discussed in Section 2.2 including behaviourist, cognitivist and constructivist approaches, and it is important to discuss their relation to and implications for e-learning. The behaviourist theory is principally concerned with learner behaviour and neglects the processes performed by the learner’s mind, as the behaviour of the learner is observed and measured to indicate what has been understood [Bechtel and Graham

1998]. Early computer-based educational systems were designed based on this approach [Ally 2004]. When designing e-learning systems following this approach, learners should be told explicitly about the learning objectives of the online lesson so that their expectations are clear and accurate judgements about their achievements can be made. Some forms of testing or other assessment can be integrated into e-learning systems to provide immediate feedback that allows learners to monitor their progress and take any corrective actions required. Appropriate sequencing of learning material according to the achievement level can also be generated in e-learning systems.

Since some educators insist that not all forms of learning can be observed or measured by the behaviourist approach, a shift toward cognitivist learning theories occurred [Ertmer and Newby 1993]. Cognitivist theory focuses on the way information is received, structured, stored and retrieved by the learner's mind, focusing on learning as an internal process [Schunk 1991]. Cognitivist approaches have several implications for e-learning systems by emphasising different learning strategies. Important information should be highlighted and placed in an appropriate place on the screen for reading and to focus the learner's attention. In addition, the difficulty level of online learning material should match the current knowledge level of the learner in order to link new information effectively with existing knowledge.

Since the learner's mind is seen as an active processor of information in the cognitivist theory, working memory should be taken into account in e-learning systems by, for instance, dividing learning material into smaller units and providing them in an appropriate sequence [Tseng et al. 2008]. Another implication for e-learning systems is that several learning strategies should be integrated to accommodate individual differences [Cassidy 2004]. Various modes of information like visual, verbal and textual should also be part of e-learning systems [Clark and Paivio 1991]. Motivation, metacognitive skills and real-life applications are important for cognitivist theory [Ertmer and Newby 1993], so e-learning systems should offer different learning strategies to motivate learners by, for instance, capturing the learner's attention at the beginning of the lesson and maintaining it, informing learners about the lesson's importance and how it can benefit them, while providing feedback on learners' performance [Keller 1987].

The constructivist theory is considered to be a branch of cognitivism, but has a specific focus, emphasising the experience resulting from the learner's interactions with the learning environment and conceptualising the learner's mind as a processor responsible for reasoning, information retrieval and reflection [Ertmer and Newby 1993]. Following the constructivist approach, e-learning systems should integrate interactive features to apply information in practical situations in order to facilitate knowledge construction. In addition, learners are responsible for their learning and how they construct knowledge. This may not be fully supported in classroom-based learning, since educational material and its sequencing normally matches the teacher's preferences, neglecting the different needs of the individual students. In contrast, e-learning systems can be enhanced by providing more relevant material when designing systems based on different characteristics such as learning style, knowledge level and skills [Ally 2004].

Other approaches that facilitate constructive learning in e-learning systems are adding collaborative and cooperative features [Magnisalis 2011], offering learners some control over the educational process, allowing for more time and providing opportunities for reflecting on and internalising information [Lin and Hsieh 2001]. Effective learner-system interaction plays an important role in developing new knowledge, skills and attitudes, so that supporting this interaction is crucial in e-learning systems [Murphy and Cifuentes 2001; Moore 1989].

3.2.3 Examples of E-Learning Systems

A large number of free, open-source and commercial e-learning systems already exist [Hauger and Köck 2007]. They have been developed and used by several organisations such as universities, schools, and even business and military sectors to support learners and to manage the learning programmes. An important example is WebCT which was developed as open source software at the University of British Columbia in 1996 and made commercially available in 1997 to create web-based learning environments. WebCT was then bought by Blackboard Inc. in 2006 and combined with the Blackboard[10] system. Blackboard has been used as an e-learning system by countless institutions around the world since 1997 [Hauger and Köck 2007]. It is a commercial product and comes with different versions that offer specific services. For example, Blackboard Learn aims to support teaching, online assessment and engagement of learners, while Blackboard Collaborate aims to provide virtual classrooms and real-time online teaching experience. However, the development of Blackboard shows no evidence of having been based on any specific learning theories [Brown 2007].

Another similar system used by many universities, colleges and schools is Canvas[12]. It comes in three different versions: Canvas Higher Ed, Canvas K-12 and Canvas Network. While Canvas Higher Ed and Canvas K-12 have obvious target audiences, Canvas Network is a new addition that aims to provide online courses delivered by different universities in a MOOC format. Courses can either be open to learners around the world or restricted to learners connected with a specific university or area. Moodle[13] is a free and open-source e-learning system founded in 2002 by Martin Dougiamas. According to the Moodle website, the development of Moodle has been influenced by the constructivist theory of learning, and is

[10] *www.blackboard.com*
[12] *www.canvaslms.com*
[13] *www.moodle.org*

now used by more than 70 million registered users from over 200 countries. Many open-source programmers have contributed to the development of Moodle, and both everyday learners and teachers can comment on or participate in making improvements to Moodle. Figure 3 presents a screenshot of the Moodle interface showing course page, navigation area, glossary and comments.

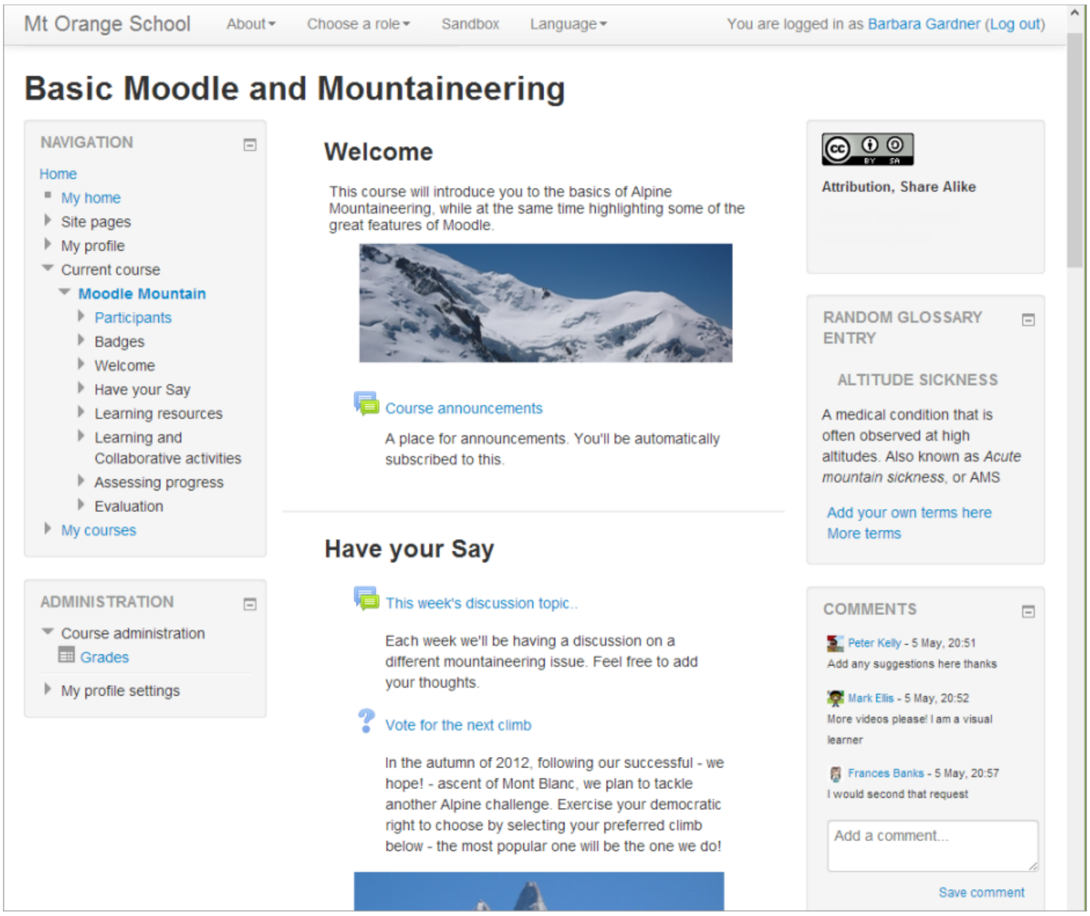


Figure 3. Interface screenshot of Moodle.

(*Software © 2013 by Mary Cooch, Moodle's Community Educator*)

In the development of another e-learning system, a number of US universities have collaborated in order to integrate their assorted learning tools and software into an open-source e-learning system named Sakai[14]. Freely available since 2005, Sakai differs slightly

[14] *www.sakaiproject.org*

from other systems by incorporating collaborative tools that support research in addition to learning and teaching. Sakai is also available in more than twenty languages including Arabic, English, French, Chinese, Russian and Turkish. Sakai is, however, designed to support only higher education.

Although there are a large number of different e-learning systems, they generally provide similar services such as creating and storing learning material by teachers using integrated, easy-to-use authoring tools, administrative and learner progress information, links to external learning resources and collaborative learning features [Brown 2007]. They often provide the ability to create tests with automatic scoring for self-assessment and social and communication tools like chat rooms, blogs and email.

3.2.4 Issues in E-Learning Systems

E-Learning systems can provide learners with many benefits such as connectivity, flexibility, interactivity and collaboration [Kruse 2002; Welsh et al. 2003]. Learners can access a large amount of information through e-learning systems anytime from anywhere eliminating, to a large extent, the temporal and physical constraints of classroom-based learning and providing a more flexible educational experience. They offer interactivity to learners, who can manipulate and interact with learning material and objects with different interactivity levels such as reading material, quizzes, taking notes and running simulations which are not always possible in classroom-based learning. Collaborative learning can also be enhanced by e-learning systems, as they provide opportunities for learner-learner interaction and learner-teacher interaction through discussion tools like forums and chat rooms. The benefits of e-learning systems encourage organisations, teachers and learners to use them [Welsh et al. 2003].

There are, however, several issues regarding learner-system interaction with e-learning systems [Hauger and Köck 2007; Shute and Towle 2003; Welsh et al. 2003]. As the review of a number of established e-learning systems in the previous section made clear, diversity of learners is not taken into account to a sufficient degree. People differ in personalities, abilities, skills, learning styles and preferences. Traditional e-learning systems do not generally take these characteristics into account in order to provide truly personalised and adaptive learning [Brusilovsky 2012]. E-learning systems may successfully retrieve different learning material and resources that technically match a specific query or goal, but they usually fail to provide the most relevant learning material that meets the different needs of individual learners [Hauger and Köck 2007]. Instead, learners have to explore, filter and organise a large amount of material; they must focus on system functionality and user instructions instead of the learning that is their primary task. In addition, a large volume of information may overwhelm learners during the learning process if they do not know when, where and what to study. This makes it difficult to process the information, leading to less effective learning. Traditional e-learning systems tend to provide the same courses and similar learning materials in the same sequence to all users, which may be problematic and lead to learner dissatisfaction and increased dropout rates [Sun et al. 2008].

A number of researchers have attempted to extend traditional e-learning systems such as LMSs by adding features to take into account the diversity of learners and provide a more personalised experience [Graf 2007; Rey-López et al. 2008]. However, this approach has so far been limited because these systems are not flexible enough and not primarily designed to support different learner characteristics [Brusilovsky and Millán 2007]. There is a need to improve and update their frameworks and models.

3.3 Adaptive E-Learning Systems

3.3.1 Introduction

Adaptivity in the context of user-system interaction is defined as an action or a process of tailoring something to meet the user's needs [Brusilovsky 2001]. For example, instructional strategies can be adapted to meet the learning styles and preferences of learners. The term personalisation is similar to adaptivity; to personalise means to design something to meet someone's individual requirements. Systems that adapt according to different user characteristics such as preferences and skills are typically called adaptive systems or user-adaptive systems [Evers et al. 2010].

Adaptive systems have been defined as "the technological component of joint human-machine systems that can change their behaviour to meet the changing needs of their users, often without explicit instructions from their users" [Feigh et al. 2012]. Jameson describes an adaptive system as "an interactive system that adapts its behaviour to individual users on the basis of processes of user model acquisition and application that involve some form of learning, inference, or decision making." [Jameson 2009].

Several studies apply adaptive technology in different domains such as e-learning, e-commerce, healthcare and digital libraries. For example, in the e-commerce domain, the MyAds system was developed to recommend advertisements with content relevant to a given user's interests [Di Ferdinando et al. 2009]. User interfaces represent another possible application of adaptivity; an example of this work is the comparison between static, adaptive and adaptable approaches to user interfaces [Findlater and McGrenere 2004]. In the e-learning domain, the iWeaver system, for instance, adapts learning material according to the learner's particular learning style [Wolf 2003]. As iWeaver shows, adaptivity can be applied in e-learning systems, which is the main focus of this thesis [Brusilovsky 1996; Jameson 2009]. Brusilovsky argues that adaptivity is highly important in order to meet the learner's characteristics such as knowledge level and learning style so that an adaptive e-learning system can provide the learner with relevant learning material and facilitate navigation through them [Brusilovsky 1996].

Adaptive e-learning systems are an enhancement to the dominant, 'one size fits all' approach to the development of e-learning systems. They are inspired by the work in both intelligent tutoring systems (ITSs) and adaptive hypermedia or web-based educational systems [Park and Lee 2003]. ITSs are adaptive educational systems that apply artificial intelligence methods and techniques to resemble the idea of one-on-one teaching [Self 1999]. In the early 1990s, the development of adaptive hypermedia or web-based educational systems began to meet the great variety and requirements of the increased number of learners who had personal computers to access information on the web.

The ultimate goal of adaptive e-learning systems is to personalise learning material and their sequences to match the needs of an individual learner as closely as possible. These systems integrate learner characteristics such as learning style, affective state and knowledge level to provide personalised services and recommend relevant instructional material [Brusilovsky 2001; Brusilovsky 2012]. A system may highlight appropriate information, recommend what that learner studies or construct personalised learning paths [De Bra and Calvi 1998; Kavcic 2004].

There are different work streams in adaptive e-learning systems [Brusilovsky 2012]. One focuses on learner modelling by representing, storing and maintaining a number of learner characteristics such as knowledge, motivation and learning style [Chrysafiadi and Virvou

2013b]. For example, Schiaffino et al. have developed a system that observes a learner's behaviour (e.g., time spent, exam results and topic studied) in order to automatically construct the learner's profile of learning style [Schiaffino et al. 2008]. Another stream deals with the development of adaptive methods and techniques. As an illustration, Brusilovsky et al. have first introduced the adaptive link annotation technique in an adaptive e-learning system; the purpose of this technique is to inform the learner of the current state of the lesson page behind the link using visual cues such as font colours, font sizes or icons [Brusilovsky et al. 1996].

Developing adaptive models and frameworks represents another work stream. For instance, De Bra et al. have developed an adaptive framework comprising components that are necessary in order to provide adaptation such as the user model, the content domain model and the adaptation model [De Bra et al. 1999]. Another important stream is concerned with content domain models and building authoring tools for adaptive hypermedia and web-based systems [Stash et al. 2004]. To demonstrate, Cristea et al. have implemented an authoring system to create and represent content so that different adaptation rules can be activated to generate personalised and adaptive lessons [Cristea et al. 2003].

3.3.2 Models and Frameworks

3.3.2.1 Introduction

Adaptive models and frameworks represent an important research area [Knutov 2012]. The adaptive framework is defined as a conceptual model that contains key components in order to generate adaptation. This section highlights some of the adaptive frameworks in order to understand their main components and how they are represented and used to provide adaptation. Jameson binds together the essential elements of adaptive systems (see Figure 4):

"A User-Adaptive System makes use of some type of information about the current individual user, such as the choices (the user) has made when (interacting with the system). In the process of user model acquisition, (the system) performs some type of learning and/or inference on the basis of the information about (the user) in order to arrive at some sort of user model, which in general concerns only limited aspects of (the user). In the process of user model application, (the system) applies the user model to the relevant features of the current situation in order to determine how to adapt its behavior to (the user)" [Jameson 2009].

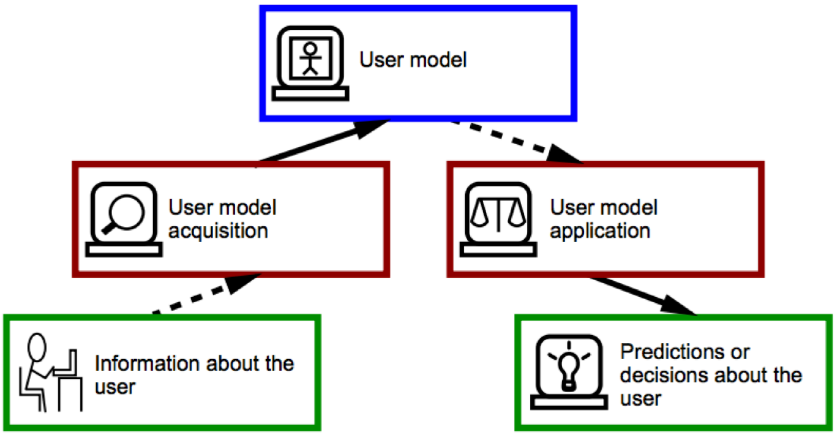


Figure 4. General Scheme of a user-adaptive system [Jameson 2009].

Adaptive models and frameworks can be used to form the design and development of adaptive e-learning systems, taking into account their main components. The core of adaptive systems reflects six central questions [Dieterich et al. 1993; Knutov et al. 2009]:

- Why do we need adaptation? (Why)
- What can we adapt? (What)
- To what can we adapt? (To What)
- Where can we apply adaptation? (Where)
- When can we apply adaptation? (When)
- How do we adapt? (How)

Articulating the main objectives and requirements of designing such a system helps answer the first question. The second question emphasises the domain model and learning content to be recommended or adapted to the different needs of learners. The third question is related to the learner model that represents, stores and maintains key learner characteristics like knowledge level, skills and learning style. The fourth and fifth questions define the context of use and the domain application area. The answer to the final question helps in determining how adaptation can be provided by taking into account different adaptive methods and techniques and how they can be implemented in an adaptive e-learning system.

Within the field of adaptive hypermedia and web-based systems, a number of models and frameworks have been proposed. One popular approach is the Dexter Hypertext Reference Model [Halasz et al. 1994], which can be used as a logical foundation for designing and comparing different hypertext systems and developing content interchange and interoperability standards. The model consists of three layers including a run-time layer, a storage layer and a within-components layer. The model emphasises the storage layer in its concern with how hypertext components and links are connected and stored in a database. The run-time layer deals with the representation of user interaction and hypertext. The within-components layer deals with the content and structure of components within a hypertext network. The Dexter model has influenced the design of many interactive web-based systems.

An extension of the Dexter model was developed to support adaptivity, called the Adaptive Hypermedia Application Model (AHAM) [De Bra et al. 1999]. AHAM enhanced the storage layer of the Dexter model by adding three sub-models including a domain model, a user model and an adaptation model. The domain model is concerned with the structure of content nodes and the links between them. The user model stores information about the system user and the adaptation model describes the mechanism of adaptation that is performed by matching the domain model objects or items to the user model characteristics, based on adaptation rules.

AHAM unified the adaptive hypermedia and web-based communities and opened the door for several technologies and development approaches for different domains of adaptive systems, including e-learning [Knutov et al. 2009]. Another model, very similar to AHAM, is the Munich Model; it differs in using the Unified Modelling Language (UML) as a formal foundation [Koch and Wirsing 2006]. A more recent enhancement of these models resulted in an advance model referred as the Generic Adaptation Framework (GAF) [Knutov 2012]. GAF is useful for different adaptation and personalisation needs, and features different components such as user, context, group and application models.

These models and frameworks all have the three fundamental components necessary for any adaptive e-learning system: a domain model, a learner model and an adaptation model. These components are each described in the following sub-sections.

3.3.2.2 Domain Model

A domain model is an abstract representation of part of the real world. It is composed of a set of domain knowledge elements [Brusilovsky 2012] and is the result of capturing and structuring knowledge related to a specific domain [Clark et al. 2012]. Knowledge types can be mainly classified as the declarative type of what something is and the procedural type of how something happens. The structure of the domain models is particularly relevant in ITSs, expert systems and hypermedia systems [Brusilovsky 2012; Brecht et al. 1989]. The content of domain models are those that are adapted to the different needs of learners in adaptive e-learning systems [Knutov et al. 2009; Sowa 2000].

A common term that is used when creating, organising and maintaining the content of a domain model is the learning object. Although the concept of a learning object is difficult to define because it has been the subject of intense debate over their scope and attributes [Anane 2014], Weller states that a learning object is a digital item of learning material that is concerned with a specific topic and that can be used in different learning environments [Weller 2007]. Anane provides a more holistic definition of a learning object as "-(1)- a digital unit of instruction, which mediates learning experiences, and -(2)- which can be discovered and accessed, and -(3)- used in a variety of instructional contexts, learning environments and computing platforms" [Anane 2014].

Learning objects are usually organised and annotated using metadata in order to describe, sequence, store and manipulate them. For example, Sun, Joy and Griffiths have proposed a novel mechanism to categorise learning objects according to the Felder-Silverman learning style model in order to dynamically provide relevant learning objects to each learner according to their learning style preferences [Sun et al. 2007].

A domain model can be represented in frame-based, network-based or logic-based scheme. A frame-based representation contains frames that have a number of attributes to describe the learning concepts [Niwa et al. 1984] and a network-based representation is formed of nodes to represent concepts and edges to represent the relationships between them. For example, a tree-like structure can be considered a hierarchical or network-based model [Gauch et al. 2007]. This representation can be flexible, easy to understand and able to trace associations between nodes. However, the ambiguity of the meaning of the nodes is difficult, as they may lead to different interpretations by different users.

A logic-based representation usually deals with procedural knowledge. It can be expressed as rules such as if-then constructions. Rules have simple syntax, are easy to understand and are highly modular and flexible. Nevertheless, they may not be sufficient for large systems, and not all types of knowledge can be expressed by rules, as they cannot help in presenting structured and descriptive knowledge.

The domain model of a number of adaptive e-learning systems is reviewed in terms of representation and application domains [Alshammari et al. 2014], and summarised in Table 3. A hierarchical network (i.e., a tree-like structure) is the most common domain model representation and may have an arbitrary number of levels. For example, a four-level hierarchical network (course, chapters, concepts and learning objects) is represented in the LearnFit system [El Bachari et al. 2011]. In a different representation, the OSCAR CITS system uses production rules of logic-based representation [Latham et al. 2012].

The content of the domain model of the reviewed systems is mainly related to computer science topics as application domains, especially programming languages [Klasnja-Milicevic et al. 2011], databases [Mitrovic et al. 2002], computer architecture and networks [Papanikolaou et al. 2003] and artificial intelligence [Schiaffino et al. 2008]. However, the LS-Plan system represents and stores material related to the history of Italian Neorealist cinema [Limongelli et al. 2009], and the domain model of TSAL contains learning material related to mathematics. Nevertheless, other application domains are still needed in future studies of adaptive e-learning systems to provide more evidence and for wider generalisation of the benefits of adaptivity [Akbulut and Cardak 2012].

Table 3. Domain model features.

System	Representation	Application domain
ELM-ART [Brusilovsky et al. 1996]	Hierarchal network: Concepts, plans and rules	Lisp programming
MASPLANG [Peña et al. 2002]	Hierarchal network: Concepts, procedures, nodes and their relationship links	Computer network: TCP/IP protocols
AES-CS [Triantafillou et al. 2003]	Hierarchal network: Concepts and topics	Multimedia technology systems
INSPIRE [Papanikolaou et al. 2003]	Hierarchal network: Goals (topics to be learned), concepts (related lessons) and educational materials (facts, procedures, exercises)	Computer architecture
iWeaver [Wolf 2003]	Hierarchal network: Seven connected lessons	Interactive multimedia and web design
TANGOW [Alfonseca et al. 2006; Paredes and Rodriguez 2004]	Hierarchal network: Tasks, sub-tasks and educational materials	Theory of computation
AHA! [Stash et al. 2006]	Hierarchal network: Concepts and their relationship (prerequisite)	Adaptive hypermedia
WHURLE-LS [Brown et al. 2006]	Hierarchal network: Lessons and learning chunks	Hypermedia systems
eTeacher [Schiaffino et al. 2008]	Hierarchal network: Course, unit, topics and reading materials	Artificial intelligence
WELSA [Popescu 2010]	Hierarchal network: Chapter, sections, sub-sections and learning objects	Artificial intelligence (Constraint satisfaction problems)
Protus [Klasnja-Milicevic et al. 2011]	Hierarchal network: Topics, lessons, and educational materials	Principles of programming (Java)
LearnFit [El Bachari et al. 2011].	Hierarchal network: Course, chapter, concept and learning object	Introduction to PHP programming
OSCAR CITS [Latham et al. 2012]	Logic-based (procedural)	SQL
LS-Plan [Limongelli et al. 2009]	Hierarchal network: Knowledge elements and associated tests	Italian Neorealist cinema
DesignFirst-ITS [Parvez 2007]	Hierarchal network: Concepts and their relationship (prerequisite)	Object-oriented design using UML

3.3.2.3 Learner Model

Learner modelling has been central to ITSs since 1970 [Self 1974]. An ITS uses the information stored in the learner model in order to adapt the way it interacts with a learner [Brusilovsky and Millán 2007]. Self states that a learner model is "what enables a system to care about a student" [Self 1999]. A number of learner characteristics can be represented and maintained in a learner model, including knowledge, goals, skills and learning style, motivation and affective state, as sources for providing adaptation [Essalmi et al. 2010]. These characteristics can be classified into cognitive (knowledge level, intellectual abilities and skills), conative (wants, intentions, goals and learning style) and affective (learner's emotions and motivation) categories [Self 1994]. Learner modelling involves different phases such as data elicitation, model representation and maintenance. Table 4 presents the learner model features of some adaptive e-learning systems which investigated the learner characteristics integration, the learning style models used and how learner characteristics are identified and updated [Alshammari et al. 2014].

For data elicitation, the learner model is usually based on explicit methods involving user-generated feedback like questionnaires and tests, or implicit methods that involve system-generated feedback like time spent, page scrolling, mouse movements and page visits [Gauch et al. 2007; Kelly and Teevan 2003]. For example, INSPIRE [Papanikolaou et al. 2003], iWeaver [Wolf 2003] and TANGOW [Alfonseca et al. 2006; Paredes and Rodriguez 2004] rely on explicit methods whereas Protus [Klasnja-Milicevic et al. 2011], WELSA [Popescu et al. 2010] and OSCAR CITS [Latham et al. 2012] use implicit techniques. A combination of explicit and implicit methods is used in eTeacher [Schiaffino et al. 2008], MASPLANG [Peña et al. 2002] and LearnFit [El Bachari et al. 2011]. The manual selection of learner preferences proposed by INSPIRE [Papanikolaou et al. 2003] and AHA! [Stash et al. 2006] assumes that learners know their learning style and preferences before interacting with the system.

Although explicit methods are considered more reliable and more accurate [Amatriain et al. 2009], learners may be reluctant to provide explicit feedback because it usually requires an extra effort by them [Agichtein et al. 2006]. In contrast, implicit methods allow learners to focus entirely on their main task and allow for capturing a large amount of data. However, data noise and the complexity of the processing, analysis and classification of data may outweigh its advantages [Kelly and Teevan 2003].

Table 4. Learner model features.

System	Learner characteristics	Learning style model	Data elicitation
ELM-ART [Brusilovsky et al. 1996]	Knowledge level	None	Explicit (questionnaire)
MASPLANG [Peña et al. 2002]	Knowledge level Learning style	Felder-Silverman model	Explicit (questionnaire)
AES-CS [Triantafillou et al. 2003]	Cognitive style	Witkin model: Field dependence and field independence	Explicit (questionnaire)
INSPIRE [Papanikolaou et al. 2003]	Knowledge level Learning style	Honey and Mumford Model	Explicit (questionnaire) Manual selection
iWeaver [Wolf 2003]	Preferences Learning style	Dunn and Dunn Model	Explicit (questionnaire)
TANGOW [Alfonseca et al. 2006; Paredes and Rodriguez 2004]	Learning style	Two dimensions of the Felder-Silverman model: Sensory-intuitive and sequential-global	Explicit (questionnaire)
AHA! [Stash et al. 2006]	Learning style	Multiple learning style models	Manual selection
WHURLE-LS [Brown et al. 2006]	Learning style	The visual-verbal dimension of the Felder-Silverman model	Explicit (questionnaire)
eTeacher [Schiaffino et al. 2008]	Learning style	Three dimensions of the Felder-Silverman model: Sensory-intuitive, sequential-global and active-reflective	Explicit (questionnaire) Implicit (learner actions)
WELSA [Popescu 2010]	Learning style	Unified Learning Style Model	Implicit (learner actions)
Protus [Klasnja-Milicevic et al. 2011]	Knowledge level Learning style	Felder-Silverman model	Explicit (questionnaire) Implicit (learner actions)
LearnFit [El Bachari et al. 2011].	Preferences Learning style	Myers-Briggs Type Indicator	Explicit (questionnaire) Implicit (learner actions)
OSCAR CITS [Latham et al. 2012]	Learning style	Felder-Silverman model	Implicit (student actions)
LS-Plan [Limongelli et al. 2009]	Knowledge level Learning style	Felder-Silverman model	Explicit (questionnaire) Implicit (learner actions)
DesignFirst-ITS [Parvez 2007]	Learning style	Felder-Silverman model	Explicit (questionnaire)

A good survey of learner modelling approaches such as the overlay, stereotype and Bayesian network over the last decade has been provided by Chrysafiadi and Virvou [Chrysafiadi and Virvou 2013b]. The key concept behind the overlay model is that the learner's knowledge is a subset of the domain as a whole [Carbonell 1970]. This representation is mostly used in adaptive e-learning systems such as MASPLANG [Peña et al. 2002], INSPIRE [Papanikolaou et al. 2003] and eTeacher [Schiaffino et al. 2008] to represent the knowledge level of learners. Although this representation is simple and powerful, its chief drawback is that it does not represent misconceptions or incorrect knowledge. Moreover, it cannot represent other learner characteristics such as preference, skills and learning style.

In another learner model representation, the idea of the stereotype model was first introduced in a system called Grundy [Rich 1989]. Stereotype models classify a group of people who share the same preferences or interests or exhibit a certain type of behaviour. Knowledge about a particular learner can be inferred on the base of stereotype(s), without explicitly going through knowledge elicitation with each individual learner. However, in the process of construction of a stereotype model, classes are usually built according to certain assumptions, and these assumptions may not always be true. In addition, this model is constructed in a handcrafted fashion before interacting with the system so that it may not be updated until a user chooses to do so explicitly. Nevertheless, a stereotype model may allow the learner model to be initiated so that adaptivity is provided quickly. For example, the stereotype representation applied in the WELSA system aims to group learners based on their learning styles [Popescu 2010].

A Bayesian network can be used to represent and maintain a wide range of learner characteristics such as emotion, learning style, knowledge and skills. It is a well-established tool based on strong mathematical foundations; it can also be implemented or integrated into an overlay learner model [Millán et al. 2010]. The eTeacher [Schiaffino et al. 2008] and LearnFit [El Bachari et al. 2011] systems, among others, rely on Bayesian networks to model learning styles. This network is classified under uncertainty-based and probabilistic models and it contains variables known as nodes and arcs to define probabilistic relationships between those variables [Pearl 1988].

Different approaches to learner modelling have also been employed. INSPIRE [Papanikolaou et al. 2003] and TANGOW [Alfonseca et al. 2006; Paredes and Rodriguez 2004] allow the logging of learner actions and interactions to infer and build the learner model. Protus [Klasnja-Milicevic et al. 2011] uses sequential pattern mining and association rules to recommend learning material based on pages visited and test results. An inferred learner model used in MASPLANG is generated from visits and time spent on learning material [Peña et al. 2002].

Investigation of the most commonly combined learner characteristics in previous efforts reveals that the majority of adaptive e-learning systems consider at most three learner characteristics in their learner models, typically, knowledge, preference and learning style [Essalmi et al. 2015; Essalmi et al. 2010]. The most common combination includes a learner's knowledge level and learning style or preferences. It thus appears that learning style and knowledge level have been deemed the most important learner characteristics to be integrated in adaptive e-learning systems [Brusilovsky and Millán 2007]. Learner knowledge is emphasised in many learning theories as a critical factor in enhancing learning in an instructional context. Learning style is also important because learners are different and they have different preferences and approaches to learning.

Although there have been many attempts to incorporate learning style in adaptive e-learning systems, selecting the most appropriate and effective learning style theory and model remains an important issue [Brusilovsky and Millán 2007]. Systems can be based on different learning style models such as the Honey and Mumford model [Honey and Mumford 1989], the Dunn and Dunn model [Dunn and Griggs 2003] and Myers-Briggs Type Indicator (MBTI) [Myers and McCaulley 1985]. However, a survey of adaptive e-learning systems that integrate learning style identified the Felder-Silverman model [Felder and Silverman 1988] as the most preferred; it was used by approximately 50% of 74 peer-reviewed articles on that subject between 2000 and 2011 [Akbulut and Cardak 2012]. Recent reviews also confirm the value in applying this model to adaptive e-learning systems [Truong 2016; Özyurt and Özyurt 2015].

3.3.2.4 Adaptation Model

The adaptation model bridges the gap between the learner model and the domain model by matching relevant learning material or sequences of learning objects to the characteristics of an individual learner [Alshammari et al. 2014]. Inspired by earlier work in adaptive graphical interfaces [Dieterich et al. 1993], Brusilovsky proposed one of the most popular taxonomies for adaptive technology, including adaptive content presentation and adaptive navigation [Brusilovsky 1996; Brusilovsky 2001]. More recently, adaptive content has been proposed as a third category [Knutov et al. 2009; Knutov 2012]. Figure 5 presents this combined taxonomy that offers a useful perspective on how to provide adaptation in adaptive systems.

Bunt, Carenini and Conati provide a comprehensive coverage of adaptive content and presentation techniques [Bunt et al. 2007], which include operations such as inserting, modifying, removing and sorting, zooming, layout changing and annotating. Adaptive navigation recommends selective learning paths and curriculum sequencing. Other examples include link generation, direct guidance and link hiding. Brusilovsky reviews many adaptive navigation techniques and illustrates them with relevant examples [Brusilovsky 2007].

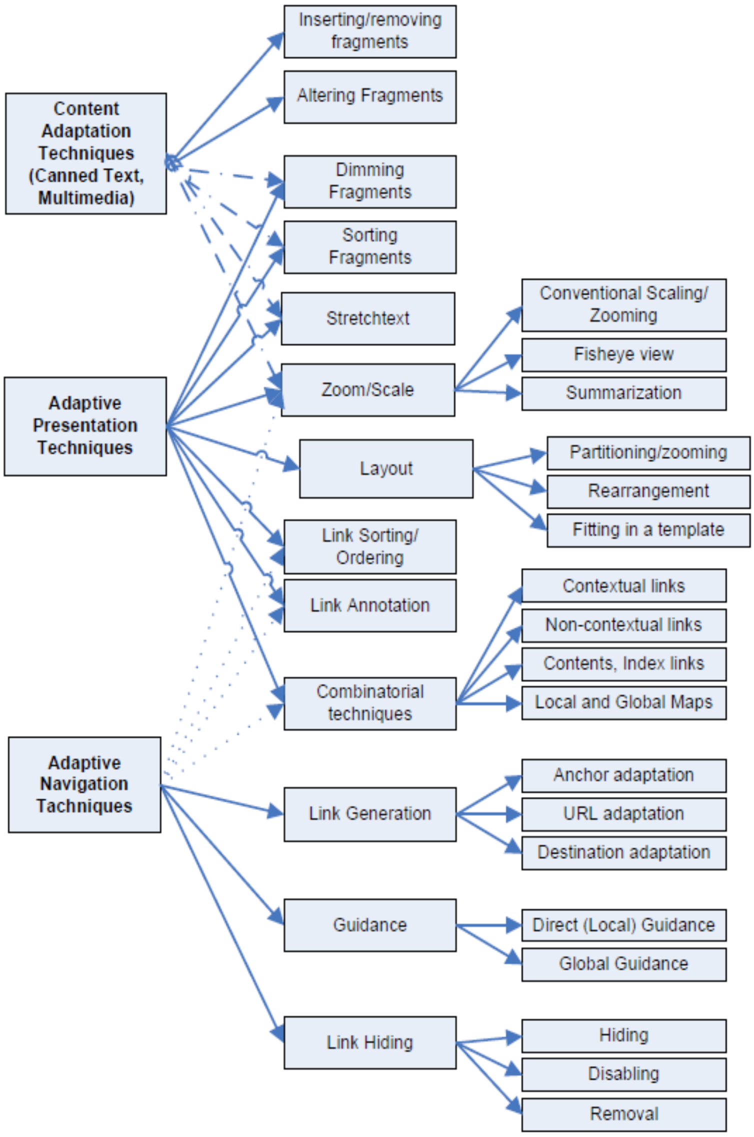


Figure 5. Taxonomy of adaptive methods and techniques [Knutov 2012].

In reviewing some of the adaptive e-learning systems as presented in Table 5, it was found that content adaptation is not sufficiently applied [Alshammari et al. 2014]. This may indicate a difficulty in applying adaptive content techniques effectively, due possibly to the effort required to author different content fragments for a specific learning concept so that the system can adapt by selecting the most appropriate fragment. This technique is known as content fragment generation and is applied in, for instance, TANGOW [Alfonseca et al. 2006; Paredes and Rodriguez 2004] and WELSA [Popescu 2010]. It may be effective in some cases; however, constructing different versions of learning material is also time-consuming. There is always a need for a human to organise material explicitly to meet adaptation rules.

Table 5. Adaptation model features.

System	Adaptive content	Adaptive presentation	Adaptive navigation
ELM-ART [Brusilovsky et al. 1996]		Link annotation Link sorting	
MASPLANG [Peña et al. 2002]		Link annotation, media format	Direct guidance, link hiding
AES-CS [Triantafillou et al. 2003]	Sorting fragment	Link annotation	Direct guidance
INSPIRE [Papanikolaou et al. 2003]		Link annotation, link sorting, media format	Direct guidance, link generation
iWeaver [Wolf 2003]		Link sorting, media format	Direct guidance, link hiding
TANGOW [Alfonseca et al. 2006; Paredes and Rodriguez 2004]	Fragment generation	Link sorting, media format	Direct guidance, link generation, link hiding
AHA! [Stash et al. 2006]	Fragment dimming, stretchtext/highlight	Link sorting, media format	Direct guidance
WHURLE-LS [Brown et al. 2006]		Media format	Direct guidance
eTeacher [Schiaffino et al. 2008]		Link annotation	Direct guidance, link generation
WELSA [Popescu 2010]	Fragment generation, fragment dimming, stretchtext/highlight	Link sorting, media format	
Protus [Klasnja-Milicevic et al. 2011]		Media format	Direct guidance, link generation
LearnFit [El Bachari et al. 2011].		Media format	Direct guidance, link generation
OSCAR CITS [Latham et al. 2012]	Conversation content		
LS-Plan [Limongelli et al. 2009]			Direct guidance, link generation
DesignFirst-ITS [Parvez 2007]		Media format	Direct guidance, link generation

Other techniques related to adaptive content are content fragment dimming and text stretching/highlighting. Content fragment dimming is usually applied to text when it is not relevant to learners as in AHA! [Stash et al. 2006] and WELSA [Popescu 2010]. Text stretching/highlighting is a useful technique and can effectively draw learners' attention to important content if it is applied appropriately [Brusilovsky 1996].

Zooming, scaling and layout-changing techniques fall into the adaptive presentation category. They are not usually considered in adaptive e-learning systems since their application to learning systems is not obvious; it depends on the situation. For instance, specific learning objects may be zoomed into for visually impaired learners whereas layout changes may be appropriate for learners using tablets and small screen devices.

Adapting media format for learners constitutes another popular technique. Satisfaction with different media formats may depend on context and domain and requires careful measurement [Alshammari et al. 2014]. To illustrate, Figure 6 presents an example of an adaptive media format in a specific lesson according to the visual-verbal learning style in the Protus system [Klasnja-Milicevic et al. 2011].

Link sorting and ordering may be more useful for non-contextual links that are not fundamentally related to the current learning object [Brusilovsky 2007]. Thus, link sorting may work with external links that lead to other information sources. It may not be appropriate to use this technique in contextual links, as it may conflict with usability standards such as consistency. Some learners may prefer the order of links and menus to be stable and to appear as they first encountered them. Link annotation may be more suitable and can be applied without interfering with usability standards to determine the current status of the concept link, such as whether it has been visited or not. ELM-ART is one of the systems that applies link annotation techniques [Brusilovsky et al. 1996].

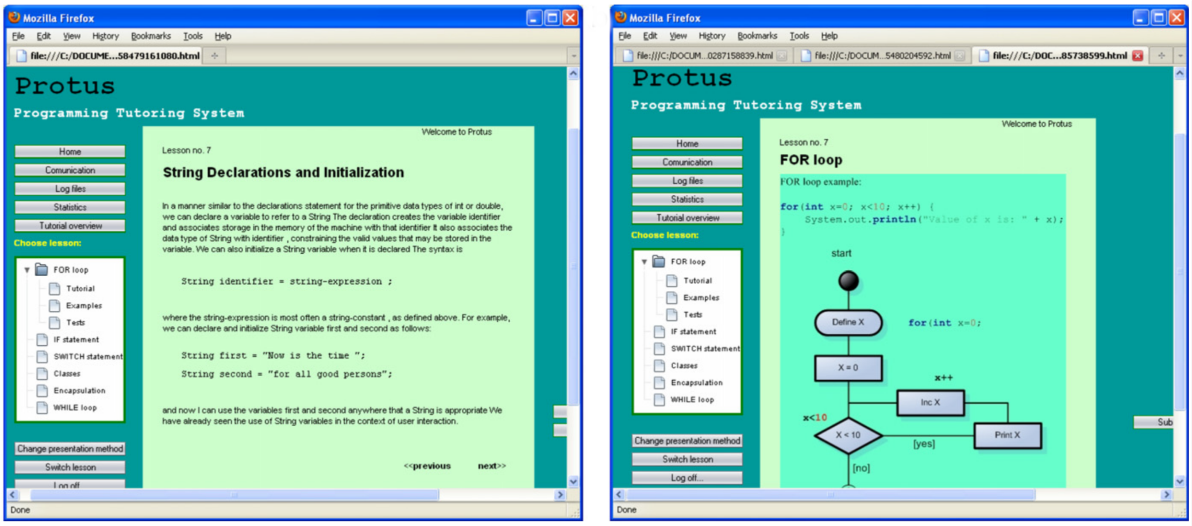


Figure 6. An example of adaptive media format based on verbal (left) and visual (right) learning styles in Protus [Klasnja-Milicevic et al. 2011].

Another classic adaptive navigation technique is direct guidance. It has been used in most adaptive e-learning systems but has been replaced by new approaches such as curriculum sequencing and personalised learning paths [Knutov et al. 2009]. This generates different learning paths for learners based on their preferences, learning style or knowledge level. Applied incorrectly, it may disrupt the learning process and disengage learners [Brusilovsky 1996]. However, the personalised learning paths have been incorporated successfully in some adaptive e-learning systems, and they may contribute to more efficient and effective learning [Chen 2008; Brusilovsky 2001; Schiaffino et al. 2008]. These adaptive techniques are considered as essential in supporting learners in adaptive e-learning systems [Shute and Zapata-Rivera 2012]. The link hiding technique is related to adaptive navigation; it removes or hides links to irrelevant pages or specific content. It may be more useful to the learning process if links are revealed gradually [Brusilovsky 2007].

The process of adaptation should not be made in isolation; instead, data on other models should be available to inform the adaptation model. The main challenge is to determine first which adaptive techniques are most effective in e-learning in the different classifications of adaptive content, presentation and navigation, and then when and how adaptive e-learning systems can provide adaptation in different cases, particularly for those that integrate learning style and knowledge level.

3.3.3 Examples of Adaptive E-Learning Systems

This section reviews current adaptive e-learning systems. It provides an overview of the existing adaptive e-learning systems that are based on the user learning style or knowledge level or the combination of the two, because of their relevance to this research and because they represent the most portion of systems [Essalmi et al. 2015; Essalmi et al. 2010]. In addition, using learning style and knowledge level to provide adaptation should enhance learning and support learner-system interaction if incorporated successfully [Akbulut and Cardak 2012; Brusilovsky and Millán 2007; Truong 2016; Mulwa et al. 2011].

Earlier work on adaptive e-learning systems began in the 1990s, which was inspired by selected features of earlier ITSs and by Web technology [Brusilovsky 1996; Self 1994]. ELM-ART was one of the first and most influential adaptive e-learning systems [Brusilovsky et al. 1996; Weber and Brusilovsky 2001], so much so that its last version, dated 2001, remains in use until today to learn Lisp programming; it adapts learning material according to each learner's knowledge level [Weber and Brusilovsky 2015]. The InterBook system was designed as an authoring tool to complement ELM-ART by creating, representing and storing learning material to be adapted to the particular learner [Brusilovsky et al. 1998]. SQL-Tutor, another example, is an intelligent tutoring system that personalises SQL learning concepts according to the individual's knowledge level [Mitrovic et al. 2002]. It was primarily intended to complement classroom-based learning in a blended learning environment and thus may not be appropriate as a standalone system for instruction.

CS383 is an early system that integrates learning style [Carver et al. 1999]. It is based on the Felder-Silverman learning style model and personalises learning material related to a computer systems course. Another example that combines two learning style dimensions of the Felder-Silverman model (*sensory-intuitive* and *sequential-global*) to personalize the presentation of learning material and their sequence is TANGOW [Paredes and Rodríguez 2002; Paredes and Rodriguez 2004]. Its application domain focuses on theory of computation, while WHURLE-LS is another adaptive e-learning system that adapts learning material related to the course 'hypermedia systems' according to only the input modality dimension (*visual-verbal*) of the Felder-Silverman model [Brown et al. 2006].

eTeacher is yet another example of a system that uses an intelligent human agent and dynamic learner modelling of learning style [Schiaffino et al. 2008], providing adaptive recommendations to support learners during their interactions with the system. Three dimensions of the Felder-Silverman model were taken into account in eTeacher: *active-reflective*, *sensory-intuitive* and *sequential-global*. OSCAR CITS is a related system that uses an intelligent approach that implicitly predicts the learning style of learners [Latham et al. 2012]. The system teaches SQL using natural language interfaces applying adaptive conversation. EDUCA adapts learning material based on the Felder-Silverman model of learning style to be used in collaborative and mobile learning environments [Cabada et al. 2011]. It is primarily designed as an authoring tool where the learning material is independent of the platform.

The systems reviewed above are all based on the Felder-Silverman model of learning style, but other systems with different foundations also exist. The AES-CS system [Triantafillou et al. 2003] is an intelligent system that recommends relevant learning material based on the Witkin model of cognitive style: *field dependence* and *field independence*. The iWeaver system, referred to above, is among the most popular systems [Wolf 2003]; it adapts different media experiences (e.g., video, text or audio) of learning concepts related to Java programming according to a learning style based on the Dunn and Dunn model. It also provides different learning tools such as note taking and simulation. LearnFit was developed in 2011 as an add-on to Moodle [El Bachari et al. 2011] and adapts learning material to support PHP programming and sequences based on learning style, taking into account the Myers-Briggs Type Indicator.

There are other systems that do not take into account a specific learning style model but combine different models. AHA! is a popular adaptive e-learning system that provides a facility for teachers to predefine instructional strategies based on a combination of different learning style models selected manually by teachers [Stash et al. 2006]. The WELSA system adapts learning material related to artificial intelligence according to the learning style of learners [Popescu 2010]. Multiple learning style models have been unified and taken into account to provide adaptation.

There is also a number of adaptive e-learning systems that integrate both learning style and knowledge level as learner characteristics that drive adaptation. MASPLANG is one of the pioneers, combining both learning style based on the Felder-Silverman model and knowledge level to adapt learning material related to a computer networking course [Peña et al. 2002]. One of the most popular and important examples of such systems is INSPIRE, an intelligent system that personalises instruction related to a computer architecture course in an online environment [Papanikolaou et al. 2003]. INSPIRE takes into account the learner's knowledge level and learning style based on the Honey and Mumford Model to generate adaptive lessons. DesignFirst ITS is an intelligent e-learning system for teaching object-oriented design [Parvez 2007], with instruction based on two learner characteristics of knowledge level and learning style based on the Felder-Silverman model.

The TSAL system takes into account learner interactions with the system and learning style in order to recommend relevant learning material related to mathematics [Tseng et al. 2008]. LS-Plan also integrates knowledge level and learning style based on the Felder-Silverman model in order to generate personalised learning paths for users [Limongelli et al. 2009]. One recent example of a successful system is Protus [Klasnja-Milicevic et al. 2011], an adaptive e-learning system based on learning style and knowledge level that recommends relevant learning material for teaching the Java programming language.

Although numerous adaptive e-learning systems have been developed, they are typically experimental laboratory platforms or used in restricted domains. Bagheri claims that there have been very few attempts to build commercial adaptive and personalised learning platforms, and provides examples of recent commercial developments such as Knewton[15], Smart Sparrow[16] and DreamBox[17] [Bagheri 2015]. The Knewton adaptive learning platform adapts learning content and instructional strategies based on the learner's knowledge level and learning style, allowing for building different adaptive applications. Smart Sparrow was built by a group of ITS researchers at the University of New South Wales[18] in Australia. Its main strength lies in providing adaptive and immediate feedback based on each learner's current level of knowledge; it is also equipped with authoring tools that allow teachers to create,

[15] https://www.knewton.com/
[16] https://www.smartsparrow.com/
[17] http://www.dreambox.com/
[18] http://www.unsw.com/

upload and store learning material in order to provide more personalised learning to their students. DreamBox teaches mathematics to elementary school students by taking into account their knowledge level and performance in a game-like learning environment.

3.3.4 Usability Issues

The idea of adaptivity in e-learning systems continues to evolve, despite the fact that it is no longer novel [Browne et al. 1990; Oppermann and Rasher 1997; Essalmi et al. 2015]. Adaptivity has been proven to be a powerful and useful concept in different domains [Brusilovsky 2001; Di Ferdinando et al. 2009; Findlater and McGrenere 2004]. Learners' preferences, knowledge and behaviour all change over time, and any system using the idea of adaptation needs to adjust to these changes. In addition, the complexity of learner-system interaction can be enhanced and simplified by adaptivity, which may overcome or at least mitigate the problem of information overload [Evers et al. 2010].

However, designing effective adaptive systems, from a usability perspective, is seen as a challenging task [Höök 2000; Norman 1994; Tsandilas and Schraefel 2004; Gena and Weibelzahl 2007]. Adaptive systems may violate standard usability principles such as privacy, consistency and learner controllability [Höök 2000; Gena and Weibelzahl 2007]. For example, inconsistent presentation and outputs of an adaptive e-learning system may be annoying or frustrating, and may not allow for equitable learning opportunities for different learners [Ashman et al. 2009]. Eliminating negative effects on usability is an essential part of the iterative design process of adaptive systems [Jameson 2009]. Ardito et al. argue that if an e-learning system is insufficiently usable, learners become frustrated and focus on the system rather than on the learning content or task [Ardito et al. 2006]. Usability represents a challenge that should be taken into account when designing and evaluating adaptive e-learning systems [Höök 2000; Benyon 1993]. There is a requirement for a better understanding of where adaptivity in e-learning systems is beneficial and where it is harmful [Ardito et al. 2006].

Although many adaptive e-learning systems have been designed and implemented, they suffer from a lack of experimental evaluation in general [Akbulut and Cardak 2012]. More particularly, usability evaluation is not usually considered as a key criterion in the iterative design process of these systems or in determining their ease of use [Orfanou et al. 2015]. Zaharias and Poylymenakou state that “very little has been done to critically examine the usability of e-learning applications” [Zaharias and Poylymenakou 2009]. It is not always clear how easy and enjoyable a given adaptive e-learning system is to use in real-world situations.

According to Bangor, Kortum and Miller, “it has become clear that a generalized assessment of the usability and customer satisfaction for different delivery types of interfaces is valuable information to have when trying to determine which technology would be best suited for different deployments” [Bangor et al. 2008]. This highlights the importance of usability evaluations of adaptive e-learning systems in particular, since learners encounter different designs and presentations of content adapted to their individual characteristics. In addition, usability investigations should be taken into account to achieve a harmony between learner, learning task, learning context and the e-learning system itself [Benyon 1993].

It is essential to note that adaptivity must be applied carefully; what works in one domain may not necessarily be appropriate for another [Van Velsen et al. 2008; Weibelzahl 2001]. Nevertheless, and despite the usability challenges of adaptivity, once applied successfully and if an adaptive e-learning system knows when, where and how to provide adaptive services to the learner, adaptivity certainly can enhance the learner-system interaction [Akbulut and

Cardak 2012; Brusilovsky 2012]. Four problems should be taken into account when applying adaptivity: usability, useful adaptation, development methods and maintainability [Höök 2000].

3.3.5 Evaluation Approaches

This section provides an overview of different evaluation methodologies that have been used in general before shedding light on how existing adaptive e-learning systems are evaluated in detail. Evaluation is defined as the "identification, clarification, and application of defensible criteria to determine an evaluation object's value, quality, utility, effectiveness, or significance in relation to those criteria" [Worthen et al. 1997]. Ensuring that an interactive system meets the requirements, produces high quality and reliable services and enhances user-system interaction represent the main factors of evaluation [Dix et al. 2004].

Evaluation methodologies of human-computer interaction (HCI) have generally been adopted for evaluating adaptive systems [Gena 2005]. A user-centred evaluation (UCE) approach is key to HCI, so it has been argued that this approach should be adopted when evaluating adaptive systems [Gena 2005; Mulwa et al. 2011]. UCE refers to evaluation of the usefulness, effectiveness, value and usability of a system to the intended end-user [Gena and Weibelzahl 2007; Van Velsen et al. 2008]. The appropriateness of a UCE approach can be justified by the facts that the main source of information is usually generated from user-system interaction and that users are the main target of adaptive systems [Mulwa et al. 2011].

Following this approach, selected evaluation methods can be taken into account [Dix et al. 2004]. One method is to collect user opinions by interviews, questionnaires and focus groups, as undertaken in a study related to the AES-CS system [Triantafillou et al. 2003]. Another method is to monitor usage by direct observation of user-system interaction, think-aloud protocols or logging use, as the MASPLANG system was evaluated [Peña et al. 2002]. Predictive evaluation is another method, usually carried out with domain or usability experts. Heuristic evaluation, expert review, parallel design and cognitive walkthrough are all different techniques in predictive evaluation. Formative evaluation, meanwhile, aims at inspecting early-stage design issues of adaptive systems; techniques involve Wizard of Oz simulation, prototyping and scenario-based design. These techniques have been applied in a study related to the ITSPOKE system [Forbes-Riley et al. 2008]. The final approach is called experimental evaluation; also known as the controlled experiment [Weibelzahl 2001], it is concerned with the effectiveness and usability of a system in structured settings to reflect genuine situations with a more controlled approach.

Although a widely accepted method for evaluating adaptive systems still needs to be developed [Chrysafiadi and Virvou 2013a], it has been argued that experimental evaluation is valuable for adaptive systems as it produces evidence of the usefulness of the adaptivity approach and provides justification of the effort expended [Weibelzahl 2001]. This is specifically advocated for adaptive systems; it can also be beneficial to inspect usability issues such as consistency and learnability [Höök 2000; Jameson 2009]. Another merit of experimental evaluation is helping to determine the advantages and effectiveness of adaptive systems with real users reflecting genuine situations to the degree possible with a more controlled approach [Gena and Weibelzahl 2007].

Concerning how adaptive e-learning systems are evaluated, some studies have not reported any result or shown any sort of evaluation, as in CS383 [Carver et al. 1999], ELM-ART [Brusilovsky et al. 1996] and iLearn [Peter et al. 2010]. However, the majority of systems have been evaluated by conducting a set of experiments – with varying quality – with learners in learning environments [Brown et al. 2009]. Some studies report on particular results in the form of charts or descriptive data as in the studies of INSPIRE [Papanikolaou et al. 2003], AHA! [Stash et al. 2006], MASPLANG [Peña et al. 2002], SQL-Tutor [Mitrovic et al. 2002] and OSCAR CITS [Latham et al. 2012].

However, there was no statistical testing carried out for evaluating the effectiveness, usability and efficiency of the mentioned systems. In addition, their sample sizes were very small. Participants were mainly undergraduate students except for the evaluation study related to the AHA! system, which combined postgraduate and undergraduate students [Stash et al. 2006]. DesignFirst-ITS was evaluated with high school students [Parvez 2007], while children aged between 9 and 11 years of age participated in a study related to the evaluation of the DEUS system [Brown et al. 2007].

Other studies related to systems including eTeacher [Schiaffino et al. 2008] and INSPIRE [Papanikolaou et al. 2003] which logged use and monitored learner-system interaction actions. These data can be analysed in order to investigate the behaviour of learners and report on system usability. The data collected could also be used to update the learner model in order to recommend relevant material. For example, an accuracy evaluation of the e-Teacher learner model for predicting learning style based on learner's interaction was conducted [Schiaffino et al. 2008]. The generated data were used to recommend relevant material based on the updated learning style, beyond their learning usefulness in evaluation. However, evaluating systems that apply dynamic learner modelling by implicit methods is more complex, prone to error and requires long learner-system interaction to build an accurate and reliable learner model [Brusilovsky 2012].

Some statistical tests were provided in other studies involving iWeaver [Wolf 2003], Protus [Klasnja-Milicevic et al. 2011], WHURLE-LS [Brown et al. 2006] and LearnFit [El Bachari et al. 2011]. Their experimental evaluations were designed and conducted reasonably well. Wolf provided one of the best examples of statistical testing for evaluating learning style-based adaptation in his work on the iWeaver system [Wolf 2003]. Appropriate attention was paid to experimental design and data analysis but the sample size however was very small.

A carefully designed experiment with more thorough evaluation and a larger sample was carried out to investigate adaptation based on learning style in the WHURLE-LS system [Brown et al. 2006]. Although it produced negative findings, it was based solely on one aspect of learning style (*visual-verbal*). However, in similar work that focused on a single aspect of learning style (*sequential-global*), there were positive findings [Bajraktarevic et al. 2003]. This highlights the problem of conflicting findings of learning style-based adaptation; it is because of the complexity created by a large number of different models and dimensions.

The evaluation study of the Protus system took into account a larger sample in a long-term study lasting for about four months [Klasnja-Milicevic et al. 2011]. Participants were randomized into two groups, experimental and control. These groups were, however, not balanced in terms of the number of participants. The control group had 100 participants and the experimental group had 340 participants. Moreover, internal validity was threatened, as the authors conducted the experiment while the system was being used alongside classroom-based learning. It is not clear whether the positive effect was caused mainly by the provision of adaptation or by the combination of classroom-based learning and the adaptive system.

Despite some evaluation efforts, recent reviews and surveys of adaptive e-learning systems confirm that a lack of robust and carefully designed experimental evaluations remains an important issue [Akbulut and Cardak 2012; Ross et al. 2010; Brown et al. 2009; Chin 2001; Özyurt and Özyurt 2015; Truong 2016]. Notably, it has also been argued that careful evaluation of adaptive e-learning systems is more important than proposing novel adaptive techniques with questionable benefits [Brusilovsky and Millán 2007]. Evaluating adaptive e-learning systems is a challenging task because of both the inherent complexity of these systems and the many variables that need to be controlled [Brown et al. 2009; Akbulut and Cardak 2012; Mulwa et al. 2011; Gena 2005]. Therefore, careful attention to experimental design and reporting of the results is vital when evaluating adaptive e-learning systems.

3.4 Research Issues

While it is true that there have been many attempts to build and evaluate adaptive e-learning systems, there is a general lack of carefully designed and controlled experimental evaluation [Akbulut and Cardak 2012; Truong 2016; Özyurt and Özyurt 2015]. Research into learning style-based adaptation has led to a large number of small-scale and short-term applications of particular learning style models to small samples of learners [Chrysafiadi and Virvou 2013b; Brown et al. 2009; Klasnja-Milicevic et al. 2011]. In addition, when learning style is taken into account in adaptive e-learning systems, it is rarely combined with other learner characteristics such as learner knowledge to provide adaptation that is followed by an empirical evaluation of their effectiveness in combination [Tseng et al. 2008].

With regards to which learning style model to take into account, Truong et al. recently reviewed studies of learning style adaptivity, and stated that almost all the relevant adaptive e-learning systems take into account learning style models that belong to the same family [Truong 2016]. This family of learning style models (described in Section 2.3.2) assumes that learning style is flexibly stable meaning that learning style can be changed but over a long time [Coffield et al. 2004]. Despite the fact that there are many learning style models, the

Felder-Silverman learning style model was found to be the most commonly used and appropriate model in adaptive e-learning systems for several reasons.

- Many researchers argue that this model is the most appropriate for e-learning [Akbulut and Cardak 2012; Peña et al. 2002; Alfonseca et al. 2006; Paredes and Rodriguez 2004; Klasnja-Milicevic et al. 2011; Schiaffino et al. 2008].
- It provides comprehensive details on its dimensions, identifies a teaching style for each dimension and comes with a reliable and validated learning style assessment tool [Graf et al. 2007; Zywno 2003; Felder and Spurlin 2005].
- This model was developed by taking into account other learning style models such as Kolb's model and the Myers-Briggs Type Indicator, so that some of its dimensions are relevant to those models [Felder and Silverman 1988].
- The dimensions of the model are independent from each other [Graf et al. 2007; Zywno 2003], allowing for the incorporation of either the complete model or specific dimensions into an adaptive e-learning system (examples provided in Section 3.3.3).

According to studies related to the model's dimensions, the input modality or *visual-verbal* dimension has been researched extensively and it has not been shown to yield significant enhancement of learning [Mayer and Massa 2003; Massa and Mayer 2006; Brown et al. 2006; Kollöffel 2012]. The information processing or *active-reflective* dimension can be supported implicitly by systems when they incorporate collaborative and interactive learning features [Jeong and Lee 2008; Zhan et al. 2011]. The information understanding or *sequential-global* dimension seems not to support learning if it is applied in e-learning systems, and may relate to the design of system interfaces [Brown et al. 2009].

There is, however, a particular dimension that has received little attention in previous work, despite the fact that a large number of systems have been developed [Akbulut and Cardak 2012; Truong 2016; Özyurt and Özyurt 2015; Feldman et al. 2014]. It is the information perception or *sensory-intuitive* dimension of learning style. This particular dimension is considered one of the most important learning style dimensions [Felder et al. 2002; Felder and Brent 2005]; it overlaps with and can be found in many different models such as the Kolb model [Kolb 1984] and the Myers-Briggs Type Indicator [Myers and McCaulley 1985]. Furthermore, it is correlated with various behavioural characteristics, learning styles, management styles and even with career aptitudes, skills and preferences [Felder and Silverman 1988; Feldman et al. 2014].

3.5 Conclusion

This chapter has discussed several issues related to e-learning systems. It has presented how technology has been used in learning since the early eighteenth century and defined e-learning's key terms. It has discussed the implications of learning theories for e-learning, reviewing a number of traditional e-learning systems and discussing their merits and limitations.

Adaptivity in e-learning systems has been presented, covering the main components such as the domain model, the learner model and the adaptation model. Adaptivity is usually proposed as a possible solution to address some drawbacks of traditional e-learning systems. The primary goal of adaptivity is to meet the different needs and preferences of individual learners in e-learning systems in order to enhance learning. Usability issues and challenges of adaptive systems have also been covered. In addition, the chapter has reviewed existing adaptive e-learning systems and investigated how they are evaluated, pointing to several issues that must be taken into consideration in future studies.

Some research gaps have been identified referring to further work needed to incorporate and evaluate a specific learning style dimension. The information perception or *sensory-intuitive* dimension of learning style based on the Felder-Silverman model has received little attention in published research. This dimension has neither been incorporated and evaluated in a carefully designed and controlled experiment as a single learner characteristic in an adaptive e-learning system nor combined with other important learner characteristics such as learner knowledge. These particular gaps are taken into account in this research.

Chapter 4. An Adaptive E-Learning Framework

4.1 Introduction

The previous chapter has covered the background of e-learning systems with different aspects of adaptivity, discussed their implications in learning and compared a number of adaptive e-learning systems based on learning style, knowledge level and based on both. Usability issues and some research issues were also identified.

This chapter presents an adaptive e-learning framework. In order to address the research questions, there is a need for a framework that can be used as a foundation to design and develop instances of adaptive e-learning systems by focusing on deferent perspectives of the domain model, the learner model and the adaptation model; three major components that are necessary to provide adaptation. As an instantiation of the framework, an adaptive e-learning system has also been designed and implemented. The main aims of the system are to validate the framework and to use as a platform to evaluate the effectiveness of the adaptive approaches that are generated by the system. The system can provide adaptation based on learning style, knowledge level or a combination of the two characteristics. The rationale behind the selection of these two characteristics is also presented.

4.2 Framework Architecture

4.2.1 Introduction

Many adaptive e-learning systems based on different architectures have been developed as presented in the previous chapter. Some systems are designed according to specific frameworks, and are tied to their use of specific technologies and the incorporation of specific learner features. Other systems are based on different reference or generic models related to the field of adaptive hypermedia or follow architectures taken from ITSs. Some systems are designed without being based on well-defined and explicit adaptive frameworks.

Generally, the design of adaptive frameworks needs to incorporate components that answer three main questions [Brusilovsky 1996]:

- What can we adapt? (What)
- To what do we adapt? (To what)
- How can we adapt? (How)

Figure 7 presents an abstract representation of the main components of adaptive systems that include a domain model (what), a learner model (to what) and an adaptation model (how).

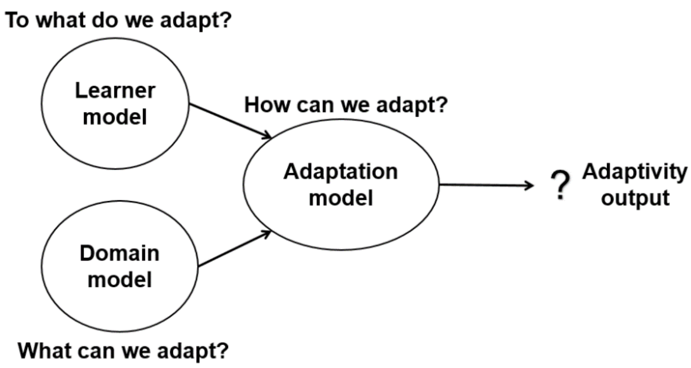


Figure 7. An abstract architectural representation of adaptive systems.

In order to address the research questions, there is a requirement for the development of an adaptive e-learning system that provides different forms of adaptation; the system can then be used for evaluation purposes. However, designing and developing an adaptive e-learning system should be based on a specific adaptive framework. The adaptive framework in the context of this work is defined as a conceptual model that contains key components in order to generate adaptation in e-learning systems. The primary goal is to provide a conceptual framework that can be used to design different adaptive e-learning systems by focusing on different aspects of the framework's components. By taking into account the questions identified by Brusilovsky when designing adaptive systems including *what*, *to what* and *how* in addition to the adaptive models and frameworks and the reviewed systems identified earlier in Chapter 3, an adaptive e-learning framework has been proposed. Figure 8 depicts the adaptive framework; it incorporates the three different facets of adaptivity. It consists of three main components including the domain model, the learner model and the adaptation model. As mentioned earlier, these components are common to many adaptive e-learning systems [Brusilovsky 2012; Alshammari et al. 2014]. There are also two auxiliary components including the interaction module and the interaction data modeller component.

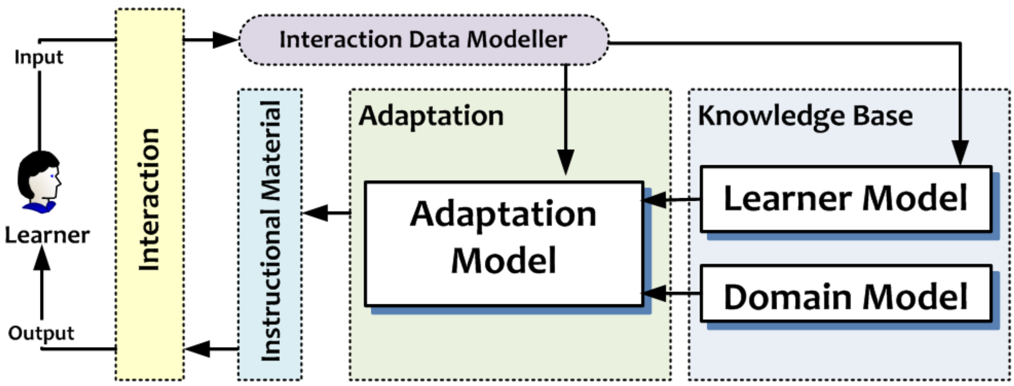


Figure 8. An adaptive e-learning framework.

4.2.2 Domain Model

The domain model stores and represents learning resources, instructional material or learning objects related to any application domain. Different representations such as network and hierarchy models can be used. The content of the domain model may be classified and annotated to facilitate the retrieval of learning resources and to support adaptation. Most application domains used in adaptive e-learning systems are usually related to computer science [Akbulut and Cardak 2012; Alshammari et al. 2014], but the domain model in the proposed framework can be flexible in terms of content, representation and management.

4.2.3 Learner Model

A wide variety of learner characteristics, including knowledge, learning style, affective state, goals, motivation, skills and context, can be integrated into the learner model [Alshammari et al. 2014; Essalmi et al. 2010]. The framework supports both static and dynamic learner modelling. Static learner models can be initiated, for instance, by completing a questionnaire to identify the learning style and by a pre-test to construct the knowledge model at the beginning of the interaction with the system; the learner's characteristics are stored in the learner model and typically left unchanged, though they can be modified manually [Paredes and Rodríguez 2002]. A dynamic approach to learner modelling continually monitors learner-system interactions to maintain a running update of the learner characteristics in the learner model [Schiaffino et al. 2008].

Adaptive e-learning systems may draw upon explicit learner feedback like rating and bookmarking, implicit learner feedback like page visits and time spent and a combination of the two to build and maintain learner models. The learner model in the framework is not limited to a specific learner characteristic, a specific learner model representation or a specific method. It implies that relevant techniques and methods can be applied to meet the requirements of the adaptive e-learning system.

4.2.4 Adaptation Model

The adaptation model takes into account the learner model and the domain model in order to adapt and recommend relevant instructional material. The adaptation model of the framework can provide two main types of adaptation: short memory cycle and long memory cycle adaptation. The short memory cycle adaptation can be achieved by processing only the most recent information elicited from learner-system interactions; for example, when a learner completes a specific quiz, the adaptation model immediately processes the learner's answers to provide adaptive feedback, hints or other instructional guidance.

The long memory cycle adaptation can be achieved by processing historical and recent learner-system interaction data to recommend relevant instructional material until the goals of the learning activity have been met. For example, if a learner rates a specific learning object as difficult, the adaptation model evaluates this recent interaction in view of past ratings of similar learning objects, then processes the data to recommend relevant learning objects. The adaptation model can incorporate different adaptive methods and techniques to support adaptation by, for example, providing different media formats, link generation and annotation techniques and by constructing personalised learning paths tailored to learner characteristics.

4.2.5 Auxiliary Components

Two auxiliary components are also included in the framework: an interaction module and an interaction data modeller. The interaction component is simply the interface which sits between the learner and the system, and is responsible for facilitating the learner's communication. The appropriate design of the system interface plays an important role in enhancing the effectiveness of learner-system interaction [Abowd and Beale 1991].

The other component, the interaction data modeller, monitors learner-system interactions, feeding into both the learner model and the adaptation model for updates. For example, if a learner visits a specific lesson page, the interaction data modeller identifies the type of this action and could then feeds it into the learner model in order to update the browsing history of the learner. The interaction data modeller also informs the adaptation model about this action in order to take recent interaction data into account when generating adaptation.

4.3 AdaptLearn: Framework Instantiation

4.3.1 Introduction

This section describes a specific instance of the framework that results in the design and implementation of an adaptive e-learning system. The system is named 'AdaptLearn', to reflect the core concept of adaptive learning. The main goals of developing AdaptLearn are to validate the proposed framework by taking into account specific perspectives of the domain model, learner model and adaptation model, and to evaluate the effectiveness of the different forms of adaptation that are generated by AdaptLearn.

The AdaptLearn system takes into account both the information perception dimension of the Felder-Silverman learning style model which classifies learners as sensory or intuitive, and the learner knowledge as learner characteristics in order to provide adaptation. The main reasons behind the popularity of the Felder-Silverman learning style model were referred earlier in Section 3.4. It is extensively used in e-learning systems [Akbulut and Cardak 2012; Truong 2016]; it provides comprehensive details on its dimensions, identifies a teaching style for each dimension and comes with a reliable and validated learning style assessment tool [Graf et al. 2007; Zywno 2003]. The dimensions of the model are independent from each other allowing for the incorporation of either the complete model or specific dimensions into an adaptive e-learning system [Schiaffino et al. 2008; Felder and Spurlin 2005; Brown et al. 2009].

The information perception or sensory-intuitive dimension has been selected in the learner model, because it is considered one of the most important learning style dimensions [Felder et al. 2002; Felder and Brent 2005; McCaulley 1990]. It also overlaps with and can be found in many different models such as the Kolb model [Kolb 1984] and the Myers-Briggs Type Indicator [Myers and McCaulley 1985]. In addition, it is correlated with several behavioural characteristics, learning styles, career skills and preferences and management styles [Felder and Silverman 1988; Feldman et al. 2014]. However, it has not been incorporated and evaluated either as a single learner characteristic in a system, or as a combination of other characteristics such as learner knowledge [Alshammari et al. 2015a]. Learner knowledge is taken into account – together with learning style – as a fundamental learner characteristic that should be integrated into the learner model in order to enhance learning [Papanikolaou et al. 2003; Klasnja-Milicevic et al. 2011].

AdaptLearn generates personalised learning paths and provides guidance and feedback as the main adaptive techniques. The generation of learning paths involves three operations on learning material links: link sorting, link hiding and link generation. The paths prioritise and sort the learning material links according to their relevance to the learner, hiding some links to material that is not relevant or not yet ready to be studied, and generating new links to material that becomes relevant as the learner progresses through learning. Personalised learning paths have been incorporated successfully in adaptive e-learning systems, and they may contribute to more efficient and effective learning [Chen 2008; Brusilovsky 2007; Schiaffino et al. 2008]. The other adaptive technique, adaptive guidance, provides learners with some recommendations such as what should be studied next and in which order, and offers feedback about the learning progress. These techniques are considered as essential in supporting learners in adaptive e-learning systems [Shute and Zapata-Rivera 2012].

The application domain of AdaptLearn is computer-related security, a crucial field in computer science [Marsa-Maestre et al. 2013]. Adaptive e-learning systems have rarely taken computer security into account in their domain models [Akbulut and Cardak 2012; Truong 2016]. Little attention has been paid in adaptive e-learning systems to support computer security education [Alshammari et al. 2015d]. In addition, this particular application domain can be beneficial to demonstrate the provision of adaptation based on learning style in particular; different types of computer security learning material such as concepts, examples, mathematical notations and practical tools can be represented and annotated in the domain model to meet the different learning style characteristics of learners. By incorporating different types of learning material, different learning abilities can also be supported such as recalling, understanding and applying, important learning factors according to the learning theories discussed earlier in Chapter 2 [Ertmer and Newby 1993].

4.3.2 System Architecture

The architecture of the AdaptLearn system is presented in Figure 9. It is based on a simple three-tier model which segments the components of AdaptLearn into three tiers of services: client, server and data storage. The client tier contains the browser interface of the system where a learner can register with the system and interact with the learning material related to a specific course that are presented by the system. The actions of the learner with the interface are passed to the server tier. For example, if the learner clicks on a link that leads to a particular learning lesson, this specific action will be delivered to and then handled by the server tier.

The server tier contains three main components: interaction data modeller, adaptation business logic and presentation logic. The interaction data modeller identifies the learner actions with the system interface, and then feeds them into the learner model and into the component of the adaptation business logic for updates. For instance, when the learner submits a quiz that is related to a specific lesson, the interaction data modeller will compute the quiz score of the learner and store the action of attempting the quiz in addition to the quiz score of the learning lesson in the learner model. The interaction data modeller also feeds the data related to this action into the component of the adaptation business logic in order to generate adaptation taking into account recent learner-system interaction data.

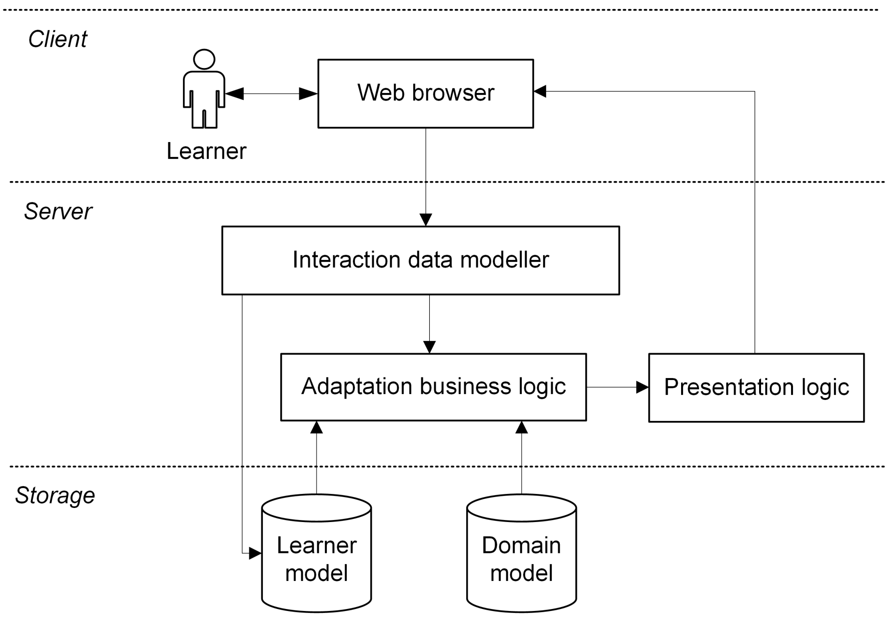


Figure 9. The architecture of the AdaptLearn system.

The adaptation business logic component contains adaptation rules that determine, for instance, what items to recommend and in which order. It is responsible for producing adaptation of instructional material. Once this component identifies the adaptation output, it feeds it into the presentation logic which specifies the way the adaptation output is displayed, and then transfers that to the client tier to be presented by the Web browser. Figure 10 presents an example of a specific learning lesson displayed on the AdaptLearn interface through the Web browser.

The data storage tier contains data related to both the learner model and the domain model. The learner model stores data about the learner such as the learning style of the learner, the number of quiz attempts, time spent on learning and what lessons were visited. This data is continually fetched by the component of the adaptation business logic to facilitate the generation of adaptation. The domain model in the data storage tier represents and stores learning material related to a specific course. The data of the domain model can also be available to the component of the adaptation business logic when required to be adapted and recommended to the learner.

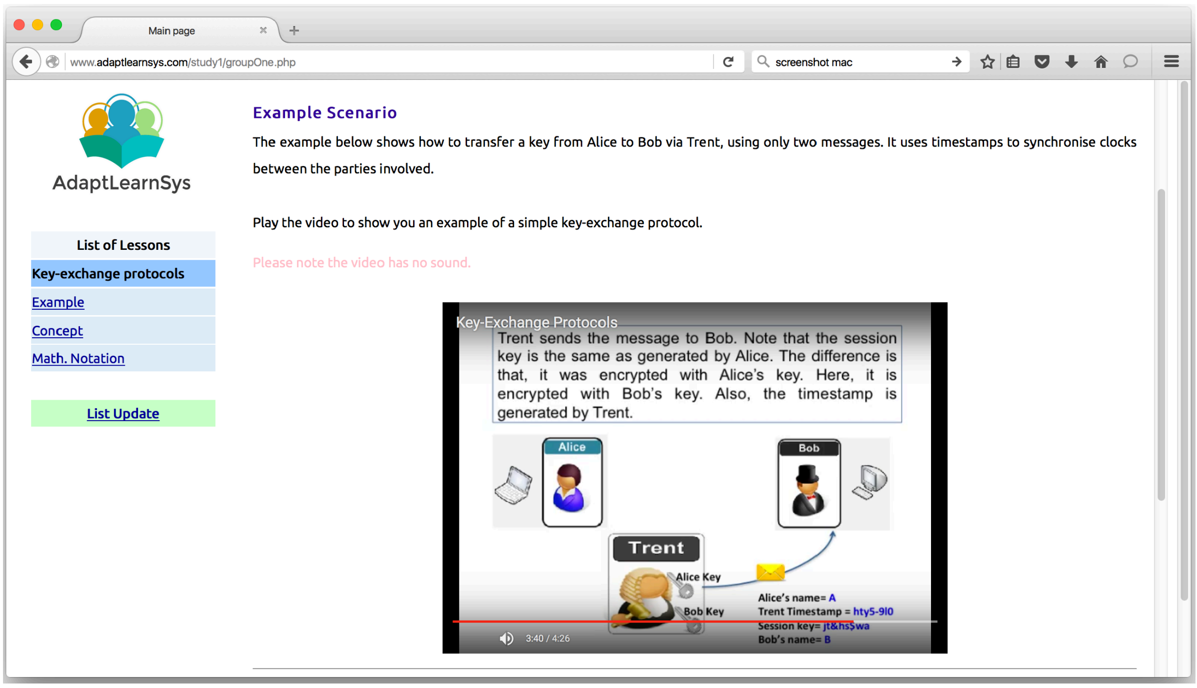


Figure 10. An example of the presentation output disiplayed by the AdaptLearn interface.

The AdaptLearn system was implemented in the NetBeans[19] development environment, which is open source and used by a large number of users and developers. It facilitates coding, running, testing and deploying different types of software applications, and also supports many programming languages. The AdaptLearn functionality was written using

[19] https://netbeans.org/

Hypertext Pre-Processor[20] (PHP), a widely used server-side scripting language for developing web applications that generate dynamic content. PHP can be deployed on many operating systems and platforms like Windows, Linux and Mac and on different servers such as Apache and IIS. PHP can be simply embedded in HTML code, or follow some specific frameworks that permit the separation between the information process to handle users' requests and responses and the information presentation in the system interface. It also supports object-oriented programming which is a style of coding in which related operations on objects are grouped into specific classes to facilitate the creation of more compact and effective code.

Since AdaptLearn is a dynamic web-based system, there should be some mechanism to represent, store, retrieve and maintain data related to the components of the system (the domain model and the learner model) and any data related to learner-system interaction in order to provide adaptation. A Database Management System (DBMS) was used; it facilitates the creation and management of a database. In this regard, MySQL[21] was used to manage the data which is an open source relational DBMS. MySQL is compatible with PHP and they interact with each other properly.

4.3.3 Domain Model

The domain model contains and represents learning material in a way that facilitates the process of recommendation and adaptation when using the AdaptLearn system. Figure 11 depicts an example of the domain model that is represented as a hierarchical network of four levels [Papanikolaou et al. 2003; Brusilovsky and Millán 2007].

Level 1 represents the course which is the root of the domain model structure. In this context, a course is made up of a series of instructional units on a particular subject. Below the course

[20] https://www.php.net/
[21] https://www.mysql.com/

node, level 2 contains a number of instructional units, each of which deals exclusively with one particular element of the course. The level of each instructional unit is classified primarily as basic, intermediate or advanced, with each category determining its appropriateness for learners according to knowledge levels.

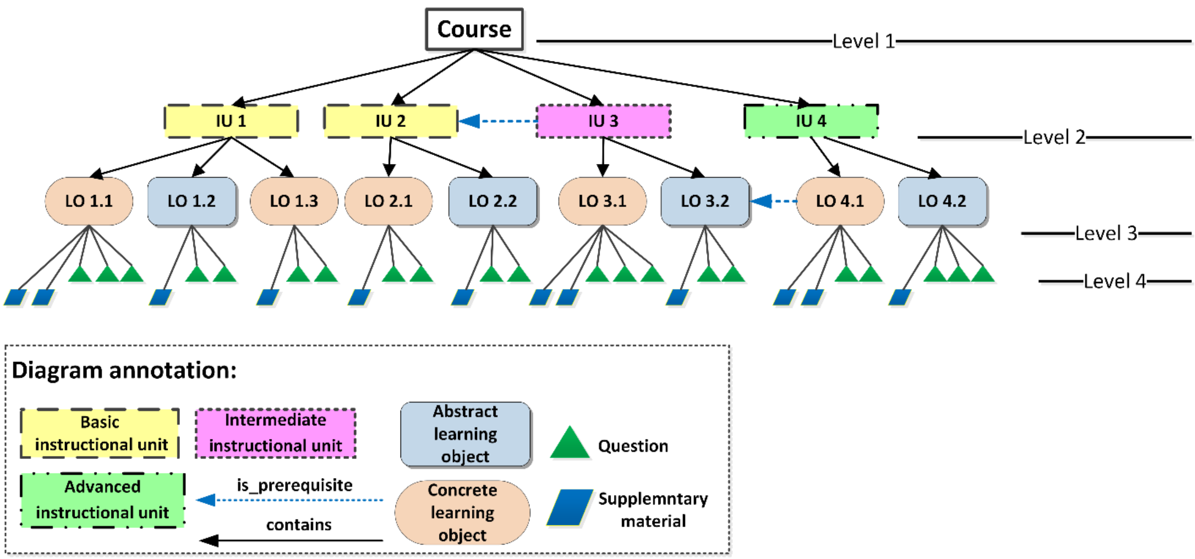


Figure 11. An example of a domain model structure (IU = instructional unit; LO = learning object).

Level 3 contains a set of learning objects (LOs) which are associated with the instructional units. Following the Felder-Silverman model, the LOs are classified and annotated according to the teaching style that corresponds to the information perception dimension of learning style. The teaching style aims to provide a combination of both concrete and abstract LOs; Concrete LOs are more suitable for sensory learners and abstract LOs for intuitive learners. Each LO is thus labelled as either concrete or abstract. Examples and practical tools are concrete, whereas concepts and mathematical notations are abstract. Figure 12 gives one example of a concrete LO and an example of an abstract LO. This is helpful when recommending and adapting the content or the sequence of LOs according to learning style.

Level 4 contains supplementary material in the form of small fragments of content and a number of test questions. Each LO is associated with supplementary material to enhance its core content with different formats and explanations, and contains a number of test questions that lead to a quiz/test directly related to that particular LO.

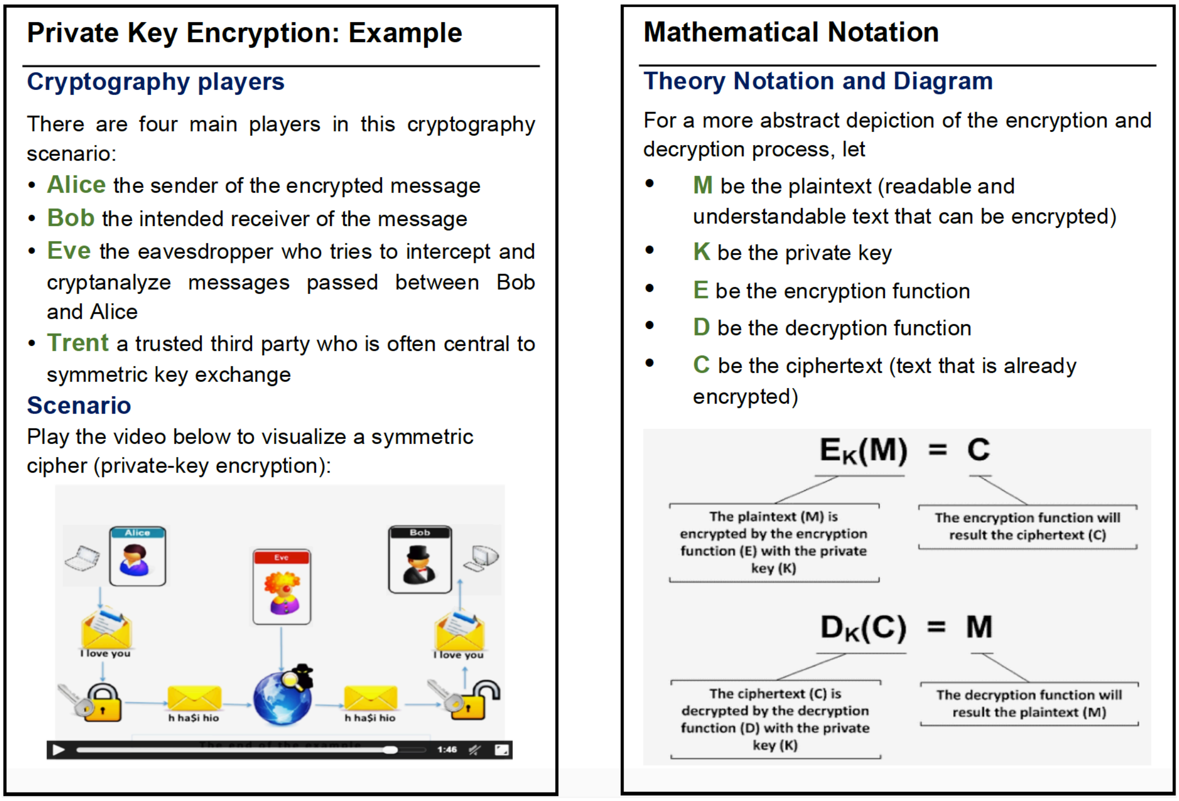


Figure 12. A concrete learning object (left) and an abstract learning object (right).

Table 6 summarises the course of computer security built into the domain model of AdaptLearn. It is comprised of three instructional units: private key encryption, public key encryption and key exchange protocols. The private key encryption unit consists of four types of LOs: concept, example, mathematical notation and practical tool. The public key encryption unit has two LOs, concept and example. The third unit, key exchange protocols, contains three LOs: concept, example and mathematical notation. Three experts in computer security have evaluated and improved the content of learning material and their associated test questions to check their validity and to ensure that they support different learning abilities such as recalling, understanding and applying; these are three critical learning aspects that should be taken into account for optimal learning [Ertmer and Newby 1993; Kolb 1984].

Table 6. The content of a computer security course represented in the domain model.

Instructional level	Instructional unit	Associated LO	LO type
Basic	Private key encryption	Concept	Abstract
		Example	Concrete
		Mathematical notation	Abstract
		Practical tool	Concrete
Intermediate	Public key encryption	Concept	Abstract
		Example	Concrete
Advanced	Key exchange protocols	Concept	Abstract
		Example	Concrete
		Mathematical notation	Abstract

4.3.4 Learner Model

Figure 13 provides an abstract representation of the learner model and its content; each learner has key personal information such as username, age, gender and email, and an associated learner style. The learner model also integrates knowledge level in order to generate tailored adaptation. Knowledge level of the entire course, of each instructional unit and of each LO – which together reflect the elements of the domain model – are maintained.

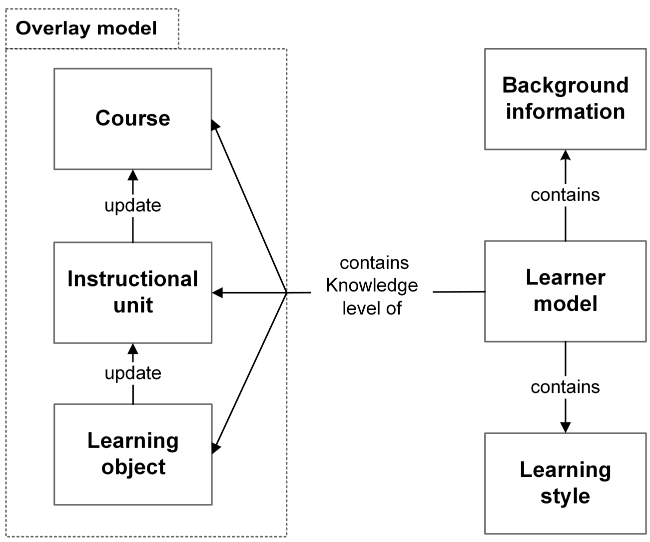


Figure 13. An abstract representation of the learner model.

Learner modelling is completed following two phases: initialisation and maintenance. Figure 14 provides a flowchart for the two phases. Initialisation is achieved through a registration step with AdaptLearn. The learner provides key personal information and completes the learning style questionnaire and a pre-test. The responses on the learning style questionnaire are used to identify the learning style of the learner, while the pre-test answers are processed to identify the learner's domain knowledge level. A knowledge level profile for each learner is initially constructed and stored in the learner model. The learner model initialisation process provides key basic data on the learner's knowledge level and the learning style.

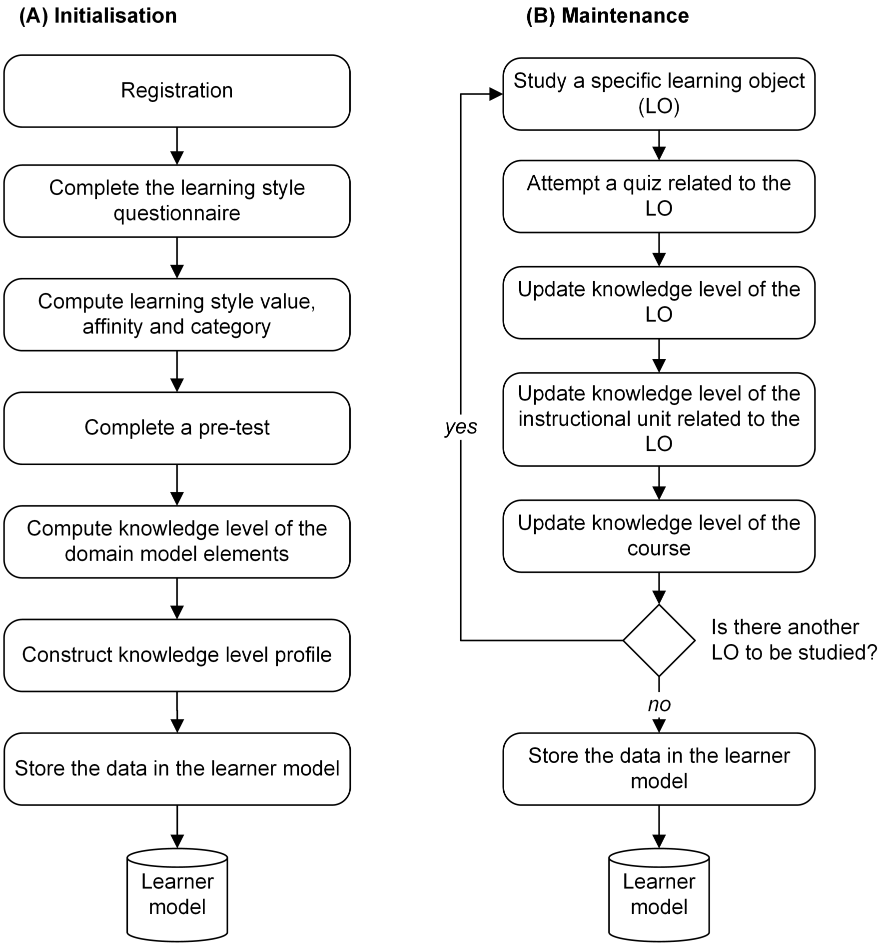


Figure 14. The two learner modelling phases of initialisation and maintenance.

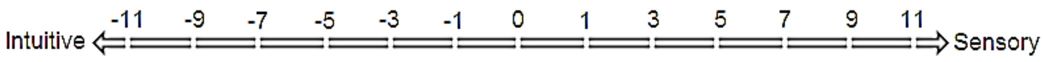
The learner model maintenance phase is accomplished with learner-system interaction, primarily by quizzes associated with each LO as the main source of interaction data. The learner model maintains only the knowledge level, while the learning style is assumed to be a more stable characteristic [Coffield et al. 2004; Felder and Silverman 1988; Kolb 1984]. When a learner finishes studying a specific LO, the system recommends a quiz to the learner.

Based on the learner's answers, the knowledge level of the related LO is updated, as are the corresponding instructional unit and course knowledge levels. The same steps are completed when studying other LOs until the primary objectives of the course have been met. The learner model keeps a running update of the knowledge level of the domain model elements (course, instructional units and LOs) based on learner-system interaction through quizzes.

4.3.4.1 Learning Style Modelling

As mentioned before, the information perception or sensory-intuitive dimension of learning style is the basis of the adaptation process. It is concerned with the type – either abstract or concrete – of learning material with which an individual learner learns best and with the best order in which to present material. It classifies learners into the two types: sensory or intuitive; learners may also have mild, moderate or strong affinities with their particular learning style. Learning style is assumed to be a generally flexibly stable learner characteristic over a relatively long period [Felder and Silverman 1988; Coffield et al. 2004; Brown 2007].

The learning style is identified through a learning style questionnaire (see Appendix A) which is regarded as a validated and reliable part of the Felder-Silverman model [Felder and Spurlin 2005]. The eleven questions related to the information perception dimension are taken into account; each question is answered by selecting either ***a*** or ***b***. Based on the responses, each learner's learning style value in the dimension and learning style category is identified. As an illustration of the determination of the learning style value, when a learner selects option ***a*** eight times, and option ***b*** three times, the learning style value is calculated by subtracting the total number of ***'a'*** responses from the total number of '***b'*** responses: 8 – 3= 5. Figure 15 presents a scale from -11 to 11 for the information perception dimension with different categories.



$$\mathrm{LS}(x) = \begin{bmatrix} 9 \text{ or } 11 & strong\_sensory \\ 5 \text{ or } 7 & moderate\_sensory \\ 1 \text{ or } 3 & mild\_sensory \\ -1 \text{ or } -3 & mild\_intuitive \\ -3 \text{ or } -7 & moderate\_intuitive \\ -9 \text{ or } -11 & strong\_intuitive \end{bmatrix}$$

Figure 15. The information perception dimension (sensory-intuitive).

A value of five indicates that it is closer to the sensory style than the intuitive style, so the learner has a sensory learning style. Each learner may have a mild, moderate or strong affinity with learning style. In this example, a value of five based on the equation LS(x) in Figure 15 indicates that the learner has a moderate sensory learning style.

4.3.4.2 Knowledge Level Modelling

Knowledge level is represented in the learner model as a knowledge overlay model (described in Section 3.3.2.3) which assumes that the knowledge of the learner is a subset of the entire domain model [Brusilovsky and Millán 2007]. This representation employs a quantitative multi-level overlay model that diagnoses and stores the degree, along a normalised scale from 0 to 100, to which a specific learner knows or understands the course as a whole, its instructional units and its LOs. The quantitative overlay model is used to overcome the problem of the pure model, which typically classifies knowledge level in a binary fashion, as either known or unknown [Brusilovsky and Millán 2007].

According to Brusilovsky, test or quiz results are reliable sources in learner modelling [Brusilovsky 1996]. As a result, the main approach used in AdaptLearn to diagnose and maintain knowledge level is having learners answer a number of test items associated with each LO. The use of tests has been successfully integrated by some systems such as INSPIRE

[Papanikolaou et al. 2003], iWeaver [Wolf 2003] and Protus [Klasnja-Milicevic et al. 2011]. Test answers are the main source of interaction data for maintaining knowledge level; for example, when a learner studies a specific LO, a quiz is recommended for the learner to attempt. Based on the learner's responses, the knowledge level of the related LO is updated to reflect the knowledge level of both the corresponding instructional unit and of the entire course. Three equations are proposed to update the knowledge level for each element of the domain model (course, units and objects) based on learner responses on quizzes. Table 7 presents these equations with brief description.

Table 7. Knowledge level equations.

Equation	Description
$\boldsymbol{LO_K} = \sum_{i=1}^{n} \boldsymbol{S_i}$	$\boldsymbol{LO_K}$ – the system's inferred knowledge level of a specific LO $\boldsymbol{i}$ – ordinal number of the question in the quiz related to the LO $\boldsymbol{n}$ – total number of questions related to the LO $\boldsymbol{S}$ – the score on the question after answering calculated as follows. $\boldsymbol{S} = \begin{cases} 100/n, & answer = correct \\ 0, & answer = wrong \end{cases}$
$\boldsymbol{IU_K} = \frac{\sum_{i=1}^{n} \boldsymbol{LO_i}}{\boldsymbol{n}}$	$\boldsymbol{IU_K}$ – the system's inferred knowledge level of a specific instructional unit $\boldsymbol{i}$ – ordinal number of the current relevant LO $\boldsymbol{n}$ – total number of LOs related to the specified instructional unit $\boldsymbol{LO_i}$ – the knowledge level of the LO i
$\boldsymbol{C_K} = \frac{\sum_{i=1}^{n} \boldsymbol{IU_i}}{\boldsymbol{n}}$	$\boldsymbol{C_K}$ – the system's inferred knowledge level of the entire course $\boldsymbol{i}$ – ordinal number of the current related instructional unit $\boldsymbol{n}$ – total number of instructional units in the course $\boldsymbol{IU_i}$ – the knowledge level of the instructional unit i

Figure 16 presents a hypothetical example of a multi-level quantitative overlay model for illustration purposes. According to the model and the instantiated values, the learner has a knowledge level of 45.33% for the course as a whole, calculated as the sum of the knowledge level of each instructional units divided by the number of units. Any update in each LO's knowledge level affects the knowledge level of its related instructional unit and therefore the entire course.

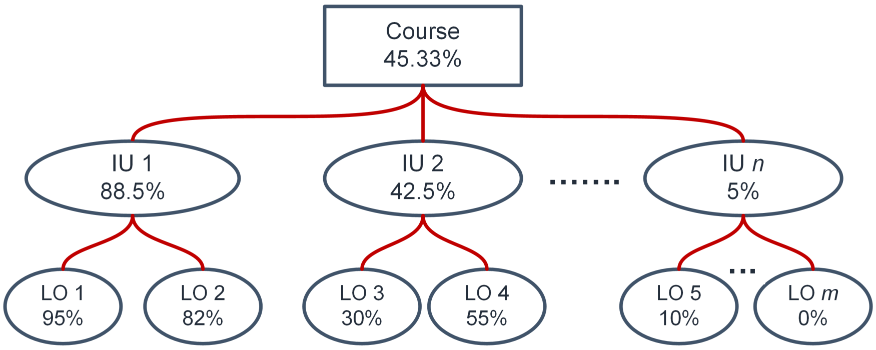


Figure 16. Multi-level quantitative overlay model for knowledge level.

4.3.5 Adaptation Model

The adaptation model aims to recommend relevant instructional material to learners to enhance their learning and satisfaction. Figure 17 depicts an abstract representation of the adaptation model. The adaptation model uses the information stored in the learner model, the domain model and the interaction data modeller in order to provide adaptation, as described earlier. The output of the adaptation model is transferred to the AdaptLearn interface to be presented to the learner. The adaptation model provides two main types of adaptive methods: personalised learning paths and adaptive guidance (explained in Section 3.3.2.4).

It should be noted that the adaptation model was implemented to provide adaptation based on learning style, knowledge level or the combination of the two characteristics. In other words, the AdaptLearn system offers a high level of adaptation based on different modes. AdaptLearn offers the ability to alternate between these modes, which is helpful in conducting different experiments to evaluate their learning effectiveness and perceived usability. For example, AdaptLearn can provide adaptation based on learning style alone, knowledge level alone and it can be configured to generate adaptation according to the two characteristics.

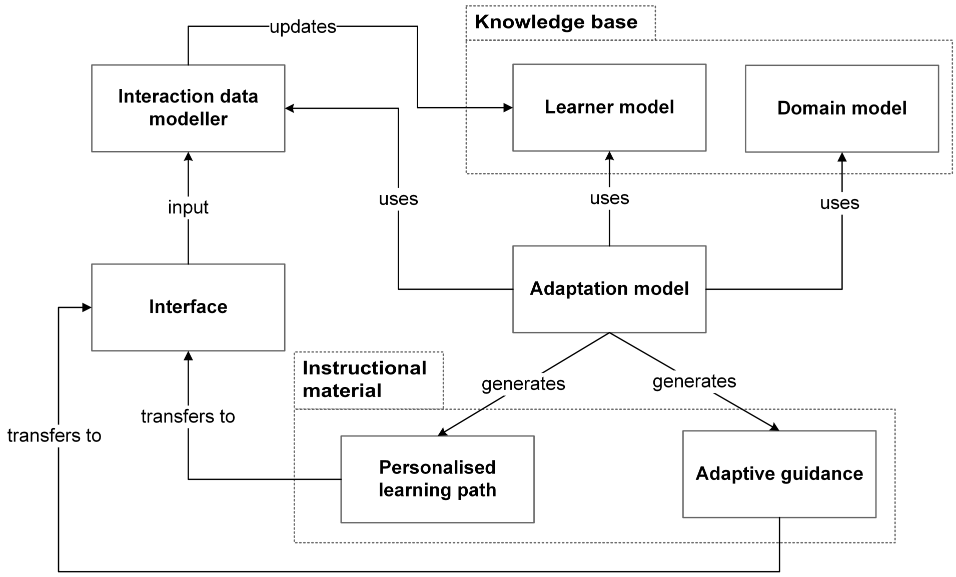


Figure 17. An abstract representation of the adaptation model.

Since learning style and learner knowledge are the main learner characteristics that are represented by AdaptLearn, the following sub-sections describe the provision of adaptation based on each characteristic.

4.3.5.1 Adaptation based on Learning Style

The adaptation model of AdaptLearn constructs personalised learning paths by taking into account the domain model and the learner model. The key feature of the learning paths is the customised sequencing and ordering of LOs based on the information perception dimension of the learning style, which classifies learners as sensory or intuitive. The pseudo code below represents the construction of personalised learning paths by the adaptation model for intuitive learners and for sensory learners. Intuitive learners study abstract LOs first and then interact with concrete LOs in an abstract-to-concrete sequence. In contrast, sensory learners start with concrete LOs and then move on to abstract LOs, in a concrete-to-abstract sequence. It is argued that learners should be provided with both abstract and concrete learning material to help them understand the learning domain [Felder and Silverman 1988]. It is not always effective to provide learners with one type of learning material [Brown et al. 2009]. In this adaptive approach based on learning style, learners interact with and study both abstract and concrete learning material but with different sequences that match their learning style. This approach meets the teaching style that is associated with the information perception dimension of the Felder-Silverman model for effective teaching.

```
Let C be the course, IU the instructional unit, LS the learning style,
LO the learning object.

For each IU in C:
      If LS = 'sensory'
            List 'concrete' LOs
            List 'abstract' LOs
      Else If LS='intuitive'
            List 'abstract' LOs
            List 'concrete' LOs
End for
```

The adaptation model constructs personalised learning paths within each instructional unit, implying that the adaptation model operates primarily on the sequence of LOs rather than on the instructional units. The default sequence of instructional units is to start with basic units, then move to intermediate and advanced units because this mode of adaptation does not take into account knowledge level but is based on learning style only.

Figure 18 gives a simple example of how learning paths are constructed across a subset of the domain model elements. For example, the private key encryption instructional unit contains four types of LOs (concept, mathematical notation, example and practical tool), which are classified as either concrete or abstract objects. The adaptation model constructs personalised learning paths based on the proposed approach. Intuitive learners study each LO as provided in the sequence of concept, mathematical notation, example and practical tool. Sensory learners follow the learning path of example, practical tool, concept and mathematical notation. Learners interact with the same LOs in both paths, but their order varies according to the information perception dimension of their learning styles.

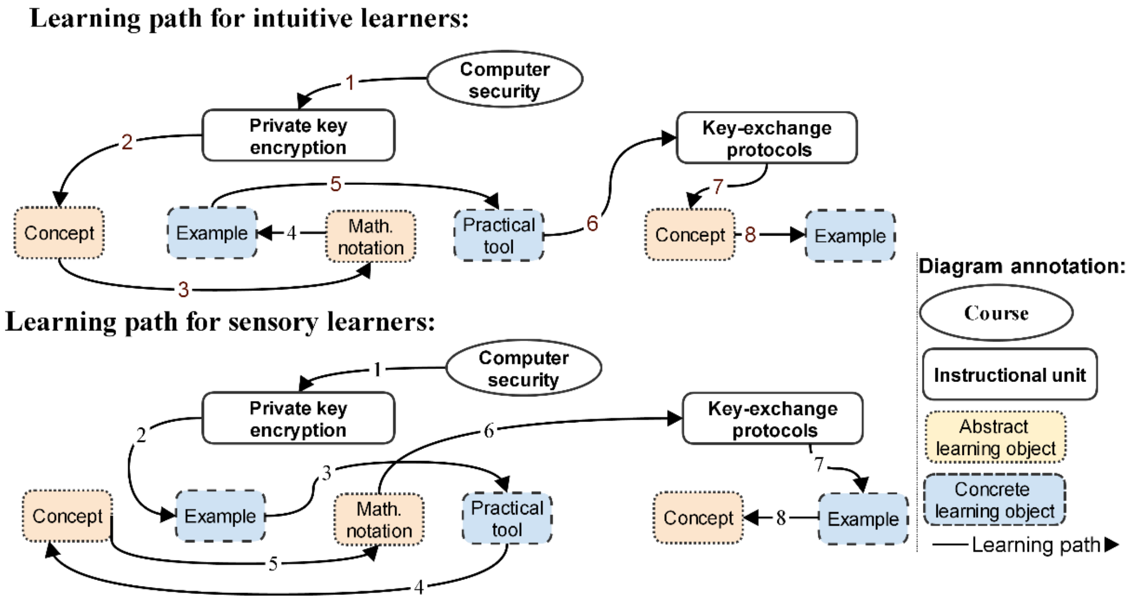


Figure 18. Learning paths constructed for intuitive and sensory learners.

4.3.5.2 Adaptation based on Knowledge Level

The adaptation model can also be configured to provide adaptation based on knowledge level. In this mode of adaptation, the adaptation model generates two types of adaptive techniques: personalised learning paths and adaptive guidance. These two techniques are detailed as follows:

Personalised learning paths. AdaptLearn constructs initial personalised learning paths for each learner based on prior knowledge as measured by a pre-test. As the learner progresses in learning, AdaptLearn takes into account both historical and recent learner-system interaction data stored in the learner model to construct new learning paths. The construction of learning paths is unique in that it operates on two levels of the domain model: the level of instructional units and the level of LOs. In the level of instructional units, the units are prioritised in the learning path according to their level of appropriateness to the course's learner knowledge level. Table 8 provides the knowledge level of the learner as retrieved from the learner model describing the associated sequence of instructional units. For example, if the course's knowledge level of the learner is intermediate, the instructional units that are classified as basic units are removed from the learning path, and the learning path prioritises intermediate units first, followed by advanced units.

Table 8. Construction of learning paths at the level of instructional units.

Knowledge level	Sequence of instructional units	Description
Beginner	basic→intermediate→advanced	If the learner is '*beginner*' according to the learner model, then the adaptation model provides basic instructional units first, followed by intermediate instructional units and lastly advanced instructional units.
Intermediate	intermediate→advanced	If the learner is '*intermediate*', then the adaptation model omits the basic units and begins with intermediate instructional units, followed by advanced instructional units.
Advanced	advanced	If the learner is '*advanced*', then the adaptation model begins with and consists only of advanced instructional units.

At the level of LOs, the personalised learning path deals principally with LOs within each instructional unit. The personalised learning path can be constructed by taking into account two main adaptive operations: adaptive removal and adaptive generation of links to specific LOs. For example, if the learner successfully completes a particular LO and the system determines that the knowledge level of that LO is satisfactory, it will be removed from the learning path; new links to specific LOs can be generated when the system determines that they become relevant as the learner progresses through learning.

Another important point is that if the learner completes the recommended learning path, a new learning path is automatically constructed. Some instructional units or LOs may be hidden or removed when the system determines that the learner would successfully complete them. New instructional units or LOs may also be added to the learning path if they were not previously considered to be suitable for the learner. The provision, removal and ordering of items in the recommended learning paths are expected to meet the needs of learners by taking into account their knowledge level characteristics so as to eliminate the effect of information overload, and to enhance their learning [Peck and Hannafin 1988; Oppermann and Rasher 1997]. The process of constructing learning paths continues until reaching an optimal case which ensures that the learner achieves the main learning objectives of the course. In other words, the learner has to complete all the LOs provided by the system, and that the learner has to have a satisfactory knowledge level of each LO in the course. When both conditions are met (i.e., completion of all the LOs and having satisfactory knowledge level of each LO in the course), the system then reaches the optimal case and no more learning paths can be constructed.

Adaptive Guidance. AdaptLearn also provides adaptive guidance based on knowledge level, which directs learners and offers recommendations as they progress towards accomplishing their current learning tasks. Adaptive guidance takes into account only the recent learner-system interaction data and processes them to provide timely adaptation. The use of tests to support learning by providing adaptive guidance and feedback is important [Sitthiworachart et al. 2008; Gikandi et al. 2011]. Therefore, the main sources of interaction data that are processed in this approach are test answers. Each test is associated with a LO, and incorrect answers to questions are taken into account to provide adaptive guidance. AdaptLearn may help the learner to understand a LO they failed by fetching related supplementary material from the domain model and then recommending it to the learner for further study, as shown in Figure 19.

Another important feature of AdaptLearn's adaptive guidance is the recommendations when modifying a current learning path or constructing a new path. These recommendations highlight the learning path elements, specify items to study and their order. Feedback on the learning progress, motivational and award messages are also provided, as shown in Figure 20.

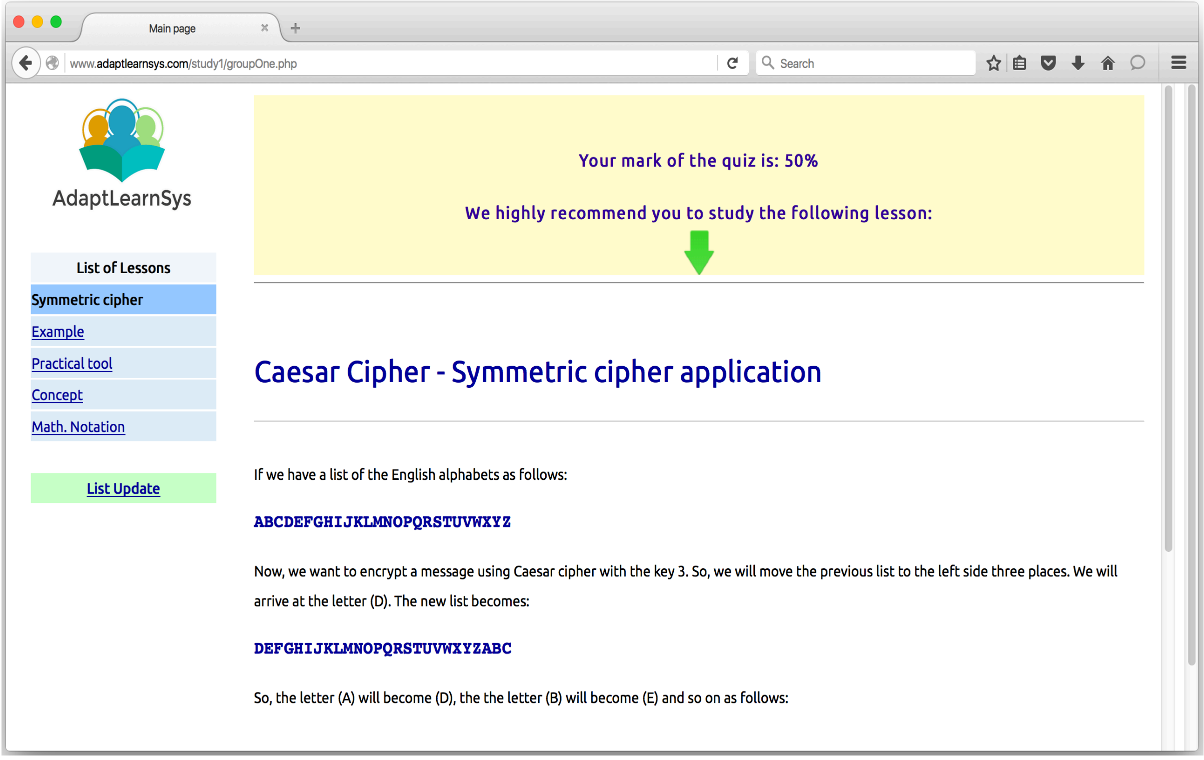


Figure 19. An example of recommendation of supplementary learning material related to a specific LO.

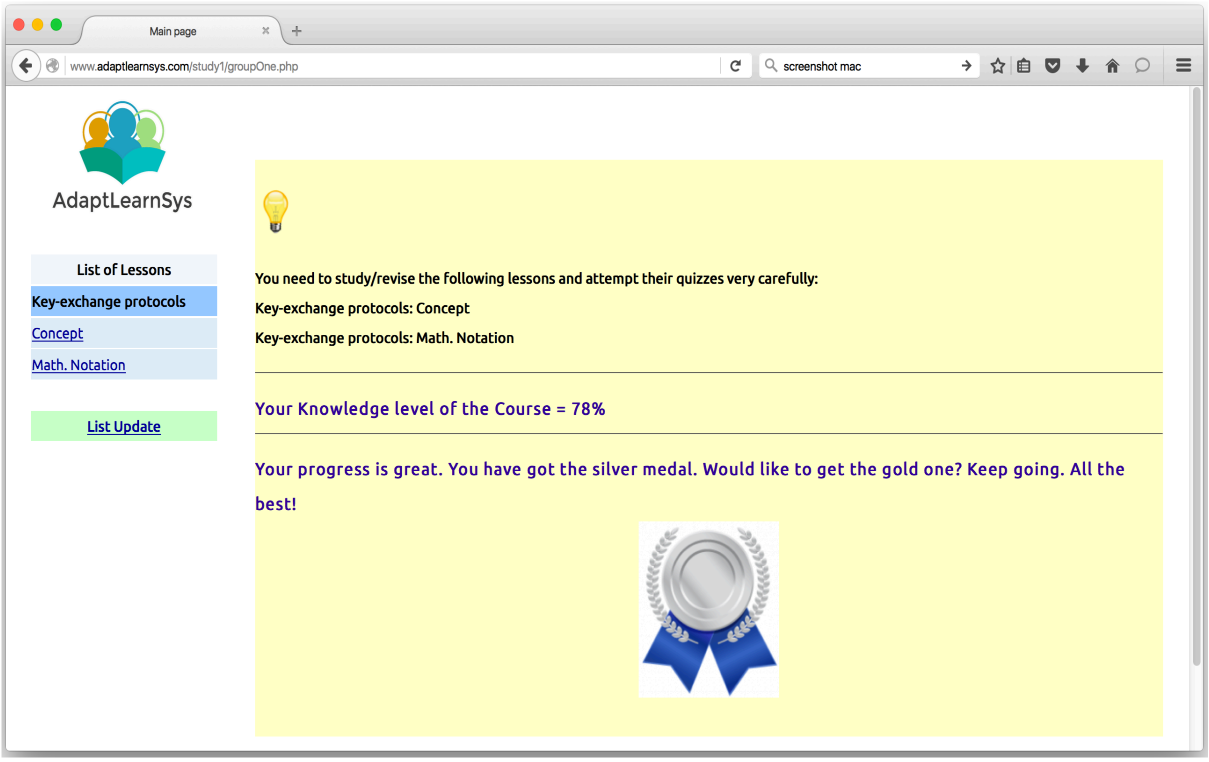


Figure 20. Recommendations, progress feedback and motivational messages.

4.4 Discussion

The proposed adaptive e-learning framework contains major components required in order to produce adaptation. It is a conceptual model which can be used as a basis to design and develop a wide range of adaptive e-learning systems. Specific instances of the framework may adopt different perspectives on the domain model, learner model and adaptation model.

An adaptive e-learning system called AdaptLearn has been designed as an instance of the framework. It takes into account two main learner characteristics – learning style and learner knowledge, in order to generate adaptation. The system is capable of providing adaptation based on learning style, knowledge level or a combination of the two characteristics. Learning style is used to construct personalised learning paths at the level of LOs. Knowledge level is used to construct personalised learning paths at the level of both instructional unit and LO. It is also used to provide adaptive guidance, such as supplying relevant additional content, offering recommendations on what to study, suggesting the sequence of study and offering feedback on learning progress.

With respect to the components of AdaptLearn, the design of the domain model is flexible enough to accommodate material related to any application domain or course. The structure of the domain model has four levels: course, instructional units, LOs and supplementary material and test questions. The domain model was constructed manually. It contains learning material related to computer security as one application domain. This particular domain is included because of its importance in computer science, and because of its limited use in adaptive e-learning systems [Alshammari et al. 2015d]. The main purpose of the domain model is to serve as a facility for storing and representing learning content in order to provide adaptation. Domain modelling is not a major part of this research, and no significant contribution is claimed in this regard. It is acknowledged that the representation of the domain model is similar to the many adaptive e-learning systems (discussed previously in Section 3.3.2.2).

With respect to the learner model, explicit learner feedback such as filling out questionnaires and answering LOs' test questions for initialising and maintaining learner characteristics are the primary techniques employed. One drawback of the explicit feedback may be that it affects the cognitive load of the learner by requiring extra effort to accomplish a specific task [Gauch et al. 2007]. However, the accuracy of explicit feedback is usually higher than the implicit feedback when building and maintaining learner models (both explicit and implicit feedback were described in Section 3.3.2.3) [Amatriain et al. 2009]. Nevertheless, answering test questions may complement and contribute to the learning process.

The learner model in AdaptLearn is based on the information perception dimension of learning style and knowledge level. In addition, according to recent learning style reviews and studies, little attention has been paid to the information perception dimension of learning style [Akbulut and Cardak 2012; Truong 2016; Alshammari et al. 2015a; Feldman et al. 2014]. As mentioned earlier, it has also been argued that this dimension represents one of the most important factors to take into account in instruction; it may correlate with various behavioural tendencies, learning styles, management styles, career aptitudes and preference [Felder et al. 2002; Felder and Silverman 1988; Feldman et al. 2014]. However, learner knowledge is a fundamental characteristic that must also be taken into account to enhance learning [Brusilovsky and Millán 2007; Papanikolaou et al. 2003; Klasnja-Milicevic et al. 2011]. As a result, learner knowledge and learning style were integrated as the primary learner characteristics into the AdaptLearn system.

The adaptation model, which represents another important component of the AdaptLearn system, provides different types of adaptive methods and techniques. Personalised learning paths are generated for individual learners. In these paths, links to learning material may be ordered, generated or hidden. The ordering, generation or removal of links are supposed to meet learner needs in order to enhance learning [Chen 2008; Brusilovsky 2007; Schiaffino et al. 2008]. Although these adaptive techniques may violate some usability standards such as consistency and learnability (discussed in Section 3.3.4) [Höök 2000], they still have significant potential to enhance learning and learner satisfaction when appropriately incorporated in adaptive e-learning systems [Ardito et al. 2006]. The provision and recommendations of learning material may help learners to accomplish their learning tasks successfully and facilitate better and more rapid understanding of learning material [Brusilovsky 2007]. Feedback, motivational messages and virtual awards are also provided according to learner progress to engage and motivate learners during the learning process [Shute and Zapata-Rivera 2012].

AdaptLearn can serve as a foundation for further development within the proposed framework. More importantly, the main goals of developing the AdaptLearn system are to:

- validate the proposed framework by taking into account the domain model, learner model and adaptation model;
- evaluate the proposed approach of learning style adaptivity by focusing on the information perception dimension of learning style;
- evaluate the effect of the combination of learner knowledge and learning style when providing adaptation;
- evaluate the perceived level of usability and its relationship with learning outcomes;
- validate the ability of the system to accommodate different learner characteristics.

4.5 Conclusion

This chapter has presented an adaptive e-learning framework which can be used to design and develop adaptive e-learning systems. It contains major components such as the domain model, the learner model and the adaptation model. The domain model is responsible for representing and storing learning material and resources. The learner model integrates, represents and maintains learner characteristics such as learning style and learner knowledge. The adaptation model bridges the gap between the domain model and the learner model in order to provide adaptation such as personalised learning paths and adaptive feedback and guidance.

As an instantiation of the framework, an adaptive e-learning system named AdaptLearn has been designed and implemented. It takes learner knowledge and learning style into account to provide adaptation. The system is capable of providing adaptation according to learning style alone, knowledge level alone and it can also be configured to provide adaptation based on both learning style and knowledge level. Alternating between these adaptive modes is possible. The main aims of the AdaptLearn system are to validate the proposed framework, to evaluate the adaptive approaches in terms of learning effectiveness and learner satisfaction, and to investigate the perceived level of usability and its relationship with learning outcome.

Chapter 5. Evaluation

5.1 Introduction

The preceding chapter has presented a framework that can be used to design and develop adaptive e-learning systems. As an instantiation of the framework, an adaptive e-learning system (AdaptLearn) was also presented and described.

This chapter deals with the evaluation of the different forms of adaptation that are generated by AdaptLearn. Evaluation is crucial for adaptive systems to ensure that they meet requirements, produce reliable and high-quality services and enhance the user-system interaction [Dix et al. 2004]. Evaluation involves the identification and clarification of selected criteria to determine the effectiveness, usefulness, value and quality of a system [Worthen et al. 1997]. Although there have been numerous attempts to build and evaluate adaptive e-learning systems as presented in Chapter 3, there is a lack of well-designed and controlled experimental evaluation examining their learning effectiveness [Akbulut and Cardak 2012; Truong 2016; Özyurt and Özyurt 2015]. Research into learning style-based adaptation has led to a large number of small-scale and short-term applications of particular learning style models to small samples of learners [Chrysafiadi and Virvou 2013b; Brown et al. 2009; Truong 2016; Akbulut and Cardak 2012; Özyurt and Özyurt 2015]. It has also been argued that a careful empirical evaluation of the effectiveness of adaptive e-learning systems is more important than proposing novel adaptive techniques with uncertain benefits [Brusilovsky and Millán 2007].

Careful design and execution of experimental evaluation and a thorough analysis and reporting of the findings represent important factors; they are taken into account when evaluating the effectiveness of adaptation in this work. The main approach used to evaluate adaptation is through carrying out experimental evaluation with actual users; this evaluation method reflects realistic learning situations to the degree possible with a fairly controlled approach. Evaluation through controlled experiments is important for adaptive systems as it produces evidence of the usefulness and effectiveness of adaptation [Weibelzahl 2001]. Experimental evaluation is concerned with the learning effectiveness, learner satisfaction and perceived usability by observation in controlled experiments [Höök 2000; Jameson 2009].

Learning effectiveness is an essential factor that should be measured when evaluating adaptive e-learning systems to determine their pedagogical effectiveness and usefulness in learning [Brown et al. 2006; Paramythis et al. 2010]. Learner satisfaction also represents another important factor in learning [Sun et al. 2008]; it is influenced by several affective factors such as motivation and engagement in the interaction, and relates to the extent to which learners believe the system they are interacting with meets their requirements [Shee and Wang 2008].

Another key factor is perceived usability, which relates to the ease of use and learnability of a specific system reflecting the extent to which users are satisfied with the interaction experience. It is expected that a high level of perceived usability when interacting with an e-learning system leads to more satisfied, engaged and motivated learners which will reflect on their learning achievement [Ardito et al. 2006; Zaharias and Poylymenakou 2009]. The three factors of learning effectiveness (short-term and long-term), learner satisfaction and perceived usability are taken into account when evaluating adaptation.

5.2 Method

5.2.1 Introduction

The AdaptLearn system can provide adaptation based on learning style, knowledge level or a combination of the two characteristics as described in Chapter 4. Several researchers insist that experimental evaluation is the most appropriate approach for evaluating adaptive e-learning systems, and that this approach is highly relevant to the criteria measured in this study, such as learning outcome, learner satisfaction and system usability [Weibelzahl 2001; Gena 2005; Brown et al. 2009; Mulwa et al. 2011]. This approach is used in this work as the main method for evaluating the effectiveness of adaptation.

It should be noted that carrying out a single experiment to evaluate the different forms of adaptation that are generated by AdaptLearn is not sufficient in the context of this work. The amount of learning time and the number of participants are limited when conducting a single experiment in addition to the difficulty in controlling and measuring different factors such as prior knowledge, learner satisfaction, perceived usability and learning effectiveness. As a result, three experiments are carried out, each with its own specific objectives and hypotheses.

Experiment 1 was designed to investigate the effectiveness of adaptation based on the information perception dimension of learning style. The experiment was controlled in terms of gender, learning material and learning time for all the experimental groups. The sample make up was homogeneous in terms of gender to control this variable. All participants in the experimental groups also interacted with the same learning material but with different sequences that matched their learning styles. By following this approach, the confounding factor of providing more learning material to a specific group was eliminated to conduct a more useful comparison. The time spent on learning was also approximately the same for the experimental groups.

Since Experiment 1 was primarily concerned with the effect of adaptation based on the information perception dimension of learning style only, a further investigation when combining the same dimension of learning style with knowledge level would generate more evidence, a deeper insight into the effect of adaptation and would also complement the results of Experiment 1. Therefore, Experiment 2 was designed to investigate the effect of three forms of adaptation on learning outcome and learner satisfaction – one based on the information perception dimension of learning style alone, one based on knowledge level alone and one based on both the information perception dimension of learning style and knowledge level. It should be noted that there could be an addition of a fourth group in Experiment 2 to serve as a control group where participants interact with a non-adaptive version of the system. However, this would require a larger number of participants; also, this was not the main aim of the experiment which is to investigate different forms of adaptation by comparing adaptation based on learning style alone, knowledge level alone and a combination of the two.

Since Experiment 1 and Experiment 2 were primarily focused on evaluating the pedagogical aspects of adaptation, there is a need to investigate the learners' perception of usability [Zaharias and Poylymenakou 2009; Ardito et al. 2006; Gena and Weibelzahl 2007; Alshammari et al. 2015b]. Experiment 3 was therefore designed to investigate the perceived level of usability and its relationship with learning outcomes by comparing a version of the adaptive system that caters to the combination of learning style and knowledge level with a non-adaptive version of the same system. The system interface and learning material were the same for both groups (adaptive and non-adaptive), with the key difference being the provision of adaptation.

A between-subjects experimental design in which each participant experiences only one condition, was used in all the three experiments; it is considered more appropriate than a within-subjects design because it avoids the problems of carryover and learning effect from one condition or factor to another, which are usually associated with a within-subjects design, in which each participant experiences more than one condition [Van Velsen et al. 2008; Gena 2005; Weibelzahl 2001]. A between-subjects design, however, requires a large number of participants, and variances between experimental and control groups may occur. Such variances should be eliminated; some variables like prior knowledge, learning style characteristics and age should be controlled as carefully as possible.

After reviewing relevant theories and research, identifying the main research questions and designing an adaptive e-learning system, the schematic process for each experiment is to (1) develop research hypotheses, (2) identify experimental variables, related data collection tools and experimental procedures, (3) select and recruit participants, (4) conduct the experiment, (5) collect and analyse data and (6) draw conclusions regarding the research hypotheses [Keppel 1991; Chin 2001].

To improve experimental results, a pilot test for each experiment was conducted with three to four participants. The main objectives of the pilot tests were to test (1) the randomisation process of participants in the experiment's conditions, (2) technical issues related to the AdaptLearn system, (3) data collection reliability and consistency, (4) the difficulty level of learning material, (5) experiment duration and (6) issues such as confusion, uncertainty and participants' questions.

5.2.2 Experimental Issues

Several important issues must be taken into account when designing experiments to evaluate adaptive e-learning systems, including external validity, internal validity and the identification of a control group that allows for the most useful comparisons with experimental conditions or groups [Chin 2001; Weibelzahl 2001]. External validity describes the extent to which findings can be generalised beyond the sample used in a study. A sample's properties are the main source of potential threats to external validity; it should be representative of the population, which can be difficult to achieve in many contexts. Finding a large number of participants is problematic and requires considerable effort, time and financial commitment. Another threat to validity is the environment where the experiment is carried out, which should always be as realistic a situation as possible.

Internal validity describes the confidence in the extent to which the change under the treatment condition in an experiment has been caused primarily by the treatment itself, and not by another factor. There are many possible threats to internal validity, including failures of prototype systems during the execution of the experiment, participants' prior experience and motivations, participant and researcher bias, system resources, the difficulty and level of learning material and the phrasing and arrangement of questionnaires.

Another consideration relates to the Hawthorne effect which is a crucial issue in experimental evaluation. Named after a set of experiments in the Hawthorne Works factory between 1924 and 1933 concerned with different interventions into physical working conditions [Brown 2007], the effect captures the observation that interventions increased productivity in the factory, irrespective of their specifics, in both the control and the experimental groups [Gillespie 1993]. The productivity increments were not necessarily caused by any specific intervention but by the awareness among participants of being under formal observation in a study. The Hawthorne effect may have an impact on the way the experiments are conducted in different contexts. It is very difficult to control, so taking part in an experiment must be voluntary with consent forms signed. In addition, using a control group, double blind and random assignment of participants in a controlled experiment may help in eliminating the possible consequences of this effect.

Another possible challenge that arises when designing experiments to evaluate adaptive e-learning systems is the identification of a control or a non-adaptive experimental condition that leads to a useful comparison between experimental groups with minimal confounding factors [Höök 2000]. Nevertheless, an adaptive e-learning system can be evaluated by investigating different forms of adaptation, and each form may be given to a specific experimental group [Paramythis et al. 2010].

5.2.3 Measurement Tools

A number of instruments and tools were used for data collection and measurements of experimental variables. Experimental variables are usually classified as dependent or independent. The former are those measured in a scientific experiment, while the latter are employed to test effects on dependent variables [Dix et al. 2004]. The independent variables in this study rely on the design of experiments and how they are conducted. Since each experiment has different but related objectives, the independent variables will be discussed when presenting the details of each experiment in later sections. The main dependent variables taken into account in the experiments are learner satisfaction, perceived level of usability and learning outcome.

The Felder-Silverman learning style model provides a reliable and validated instrument called the Index of Learning Style (ILS) questionnaire for identifying the learning style of learners [Zywno 2003; Graf et al. 2007; Felder and Spurlin 2005]. The ILS contains forty-four questions each with two possible answers, and each dimension of the model has eleven questions; the eleven questions related to the information perception dimension were used (see Appendix A). This dimension is integrated in the AdaptLearn system as a basis for providing adaptation.

Learner satisfaction is measured by a reliable, validated conceptualisation of e-learner satisfaction (ELS) tool [Wang 2003; Shee and Wang 2008], which is a questionnaire that measures both overall satisfaction and satisfaction related to specific factors of e-learning systems, including system interface, learning content, personalisation and learning community. The instrument consists of seventeen questions with 7-point Likert scales, with anchors ranging from "strongly disagree" to "strongly agree" (see Appendix B). ELS is applicable to a wide variety of e-learning systems and can be adapted to fit specific research needs [Wang 2003]. Four questions related to satisfaction with learning community were omitted, since learning community has limited relevance to the implemented system.

Usability is measured by using the system usability scale (SUS) questionnaire [Brooke 1996], a quick, reliable and widely used test of system usability in both academia and industry [Tullis and Stetson 2004]. SUS has 10 questions, each offering five responses with anchors ranging from “strongly disagree” to “strongly agree” (see Appendix C). SUS provides a single score on a scale that is easy to understand to measure overall usability. The score ranges between 0 and 100; the higher the score, the better the usability. Satisfactory systems should have a score between 70 and 80, while a score higher than 90 indicates an exceptionally usable system [Bangor et al. 2008].

Learning outcome is usually measured by tests in related work, including a pre-test, post-test and follow-up test [Akbulut and Cardak 2012; Brusilovsky and Millán 2007; Gena 2005]. The creation and improvement of tests used in this study involved three experts to check content validity and to ensure that they measure different learning abilities like recalling, understanding and applying, abilities identified as important according to the learning theories discussed earlier in Chapter 2 [Ertmer and Newby 1993]. A sample of the test questions is shown in Appendix D. Each question has five options, with the fifth option being "I do not know". This particular option is included in questionnaires to reduce the chance of random guessing [Pallant 2013].

Participants complete pre-tests before interacting with the adaptive e-learning system to determine their prior knowledge level. Post-tests are taken immediately after completion of the course to determine what the participants have learned. Follow-up tests are similar to post-tests, but are provided after a period of time has elapsed to examine the sustained knowledge of participants and any delayed effects on learning outcome. The term "learning outcome" can be measured using a pre-test and an *immediate* post-test. The variables used throughout the experiments to report on this type of learning outcome are either "Learning outcome" or "$\text{LearningOutcome}_{\text{immediate}}$". In general, it is calculated as follows:

$$\text{LearningOutcome}_{\text{immediate}} = \text{the score of the post-test} - \text{the score of the pre-test}$$

Learning outcome can also be measured using a pre-test and a *delayed* post-test, which we call a follow-up test, that is given after some weeks have elapsed. The variable "$\text{LearningOutcome}_{\text{delayed}}$" refers to this type of learning outcome when reporting data. In general, it is calculated as follows:

$$\text{LearningOutcome}_{\text{delayed}} = \text{the score of the follow-up test} - \text{the score of the pre-test}$$

5.2.4 Data Analysis

Once a set of data is collected from the experiment, it should be cleaned before beginning the data analysis process. It is inappropriate to include incomplete data in the overall data analysis. The processing or transformation of data may also be required, depending on the experimental variables. For example, a variable may be calculated based on existing data which belong to other variables. The data can be analysed once data cleaning and processing have been completed. The IBM SPSS statistical software package was used for the data analysis throughout this study.

A number of statistical tests were carried out on the dataset to obtain probability values to determine if the results are statistically significant. The conduct of tests in this study varies according to the type of data being analysed, the number of experimental groups and the specific research question being answered. Statistical tests and techniques typically investigate either the difference between experimental groups or explore relationships between variables [Gray 2014; Pallant 2013].

Differences between experimental groups are usually explored using Student's t-tests, Mann-Whitney U tests, and analysis of variance (ANOVA). If there are two experimental groups or two independent variables, t-tests are more suitable when data are normally distributed, while Mann-Whitney U tests are more appropriate for non-normally distributed data. To assess the normality of data, the Shapiro-Wilk test is used as it can handle very small sample sizes (<50) and sample sizes as large as 2000 [Pallant 2013].

If there are two or more experimental groups, a one-way ANOVA test can be run to determine whether there are any significant differences between the means of the results for each group. However, ANOVA cannot determine which specific groups differed significantly from one another. A post-hoc test such as the Tukey test is needed to compare groups in a pairwise fashion to determine where the differences lie. The resulting statistics show the significance of the findings. Probability values are generally used to measure significance at the level of 0.05 or less (i.e., 5% or a probability of 1 in 20). For example, if $p > 0.05$ is found then the finding is not considered statistically significant and may be attributable to chance rather than to the treatment under examination in the experiment.

It is also crucial to report on the importance of findings using an objective measure known as effect size [Cohen 1992]. Despite the value of reporting effect size for meta-analysis and comparisons of studies, very few studies concerning adaptivity in e-learning systems report on effect size [Brown et al. 2009; Gena and Weibelzahl 2007]. Examples of frequently used effect size measures are Cohen's d and partial eta squared ($\eta_p 2$). For Cohen's d, an effect size of 0.2 to 0.4 is small, around 0.5 is medium and 0.8 or more indicates a large effect [Cohen 1992].

Correlation statistical tests assess the extent to which two variables relate to each other and determine whether the association between the two variables is positive or negative [Pallant 2013]. It is important to note that a greater value of an association between two variables does not necessarily mean that there is a cause-and-effect relationship between them, only that a relationship does exist.

5.3 Experiment 1: Learning Style Adaptivity

5.3.1 Introduction

This section is concerned with the evaluation of adaptation based on learning style as generated by AdaptLearn, which provides customised sequences of learning objects based on the information perception dimension of learning style. As mentioned earlier, this particular dimension has received scant attention in published research, even though it is one of the most important learning style dimensions and is relevant to different learning style models.

A controlled experiment was conducted to investigate whether matching the sequence of learning objects to the information perception dimension of learning style enhances learning outcome and learner satisfaction, compared to a mismatched sequence. The main reasons for the choice of matching/mismatching approach in evaluating learning style adaptivity are as follows:

- The simple distinction between the matched and mismatched approaches can be easily and objectively defined and measured;
- It can be clearly understood and implemented in e-learning systems;
- It eliminates the possible confounding factors related to learning material where learners study the same learning material in both the matched and mismatched approaches but with different sequences;
- It represents a central difference between sensing and intuition information perception styles.

The research question investigated in this experiment is:

RQ. Does adaptation based on the information perception dimension of learning style enhance learning and does it lead to a high level of learner satisfaction?

5.3.2 Hypotheses

Two hypotheses were put forward for this experiment:

H1.1: Matching the sequence of learning objects to the information perception dimension of learning style in AdaptLearn yields significantly better *learning outcomes* compared to a non-matching sequence.

H1.2: Matching the sequence of learning objects to the information perception dimension of learning style in AdaptLearn yields significantly better *learner satisfaction* compared to a non-matching sequence.

Following these hypotheses, two experimental conditions or groups were proposed, a matched group and a mismatched group. The former interacts with a version of AdaptLearn that matches the sequence of learning objects to the information perception dimension of learning style, while the latter interacts with the same system but with a mismatched sequence. The system interface and learning material were the same for both groups, with the key difference being the sequence of the learning objects. The description of how AdaptLearn provides adaptation based on the information perception dimension of learning style can be found in Chapter 4.

The dependent variables measured in this experiment were learning outcome (measured by using a pre-test and an immediate post-test) and learner satisfaction.

5.3.3 Procedure

The experiment was conducted in eight experimental sessions, each lasting for about 75 minutes at the University of Hail, Saudi Arabia. In each experimental session, participants were introduced to the main objectives of the experiment and informed of the procedure. They were asked to access the AdaptLearn system through an Internet browser and completed a demographic data form and the Index of Learning Style questionnaire using the system.

The system then randomly assigned participants to an experimental (matched) group or a control (mismatched) group and directed them to complete a pre-test. The next step involved the study of learning material on computer security, the application domain of the system. At the end of the learning session, the participants immediately completed a post-test, followed by the learner satisfaction questionnaire.

5.3.4 Results and Discussion

5.3.4.1 Introduction

The experiment was conducted with 60 male participants; 29 participants were assigned to the matched group and 31 participants to the mismatched group. The group of participants was homogeneous in terms of culture, gender and language. The participants were undergraduate students in a computer science degree programme. The mean age of the participants was 25.27 (SD = 5.49), the maximum age was 39 and the minimum age was 18. The participants were encouraged to take part in the experiment in order to learn new topics related to computer security, which was not part of their curriculum.

There were more sensory learners (71.67%) than intuitive learners (28.33%); the majority of the participants had mild to moderate learning style characteristics, and very few participants had strong characteristics in either the sensory and intuitive categories. Figure 21 presents the percentages of participants in the sub-categories (mild, moderate and strong) of the information perception dimension.

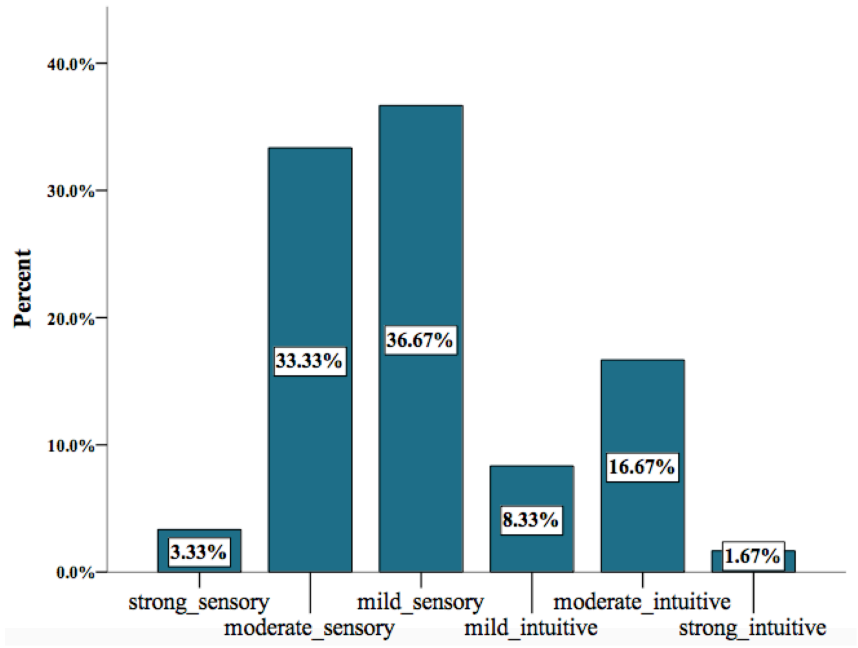


Figure 21. Experiment 1: Distribution of participants in the information perception dimension.

5.3.4.2 Learning Outcome

Hypothesis H1.1 which is about learning outcome was tested. Table 9 shows that the post-test and the learning outcome (i.e., post-test score – pre-test score) of the matched group were higher than those of the mismatched group. The findings indicate that there was generally a positive effect in matching the sequence of learning objects to the information perception dimension of learning style in AdaptLearn.

Table 9. Pre-test, post-test and learning outcome results of the matched and mismatched groups.

Group	N	Pre-test		Post-test		Learning outcome	
		Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Matched	29	10.14	14.35	43.52	22.03	33.38	19.41
Mismatched	31	18.13	18.33	38.29	19.42	20.16	26.64

However, there was a difference between the matched group and the mismatched group in terms of the pre-test results, because the random assignment of participants to experimental groups made it difficult to control the prior knowledge variable. Computer security was a new topic for 95% of the participants, based on their self-assessment. In addition, the post-test score for the matched group was still higher than the post-test score for the mismatched group.

The significance of the learning outcome was also tested. As there was homogeneity of variance between the matched and mismatched groups as assessed by Levene's test for the equality of variances, $F = 3.94$, $p = 0.06$ and data were normally distributed, an independent sample t-test was run using an alpha level (α) of 0.05. Examination of the means of learning outcome indicated that the matched group had significantly higher learning outcomes than the mismatched group, $t(58) = -2.18$, $p = 0.03$, $d = 0.57$. In addition, the effect size of the finding was between medium and large. H1.1 is therefore confirmed, and it can be concluded that matching the sequence of learning objects to the information perception dimension of learning style in AdaptLearn yields significantly better learning outcome than mismatching.

This finding relates to learning outcome measured by using a pre-test and an *immediate* post-test. A second research question involving a post-test delayed until a number of weeks or months have elapsed could also offer valuable results. While the participants in this experiment were not available to complete a delayed post-test, this issue was taken into account in Experiment 2.

The findings of the present study support the results of other studies that do support the notion of adapting to learning style [Limongelli et al. 2009; Akbulut and Cardak 2012]. Ford and Chen argue that matching learning material presentation based on the field dependence or independence of the Witkin model yields significantly better learning performance than mismatching [Ford and Chen 2001]. Bajraktarevic et al. carried out a similar study that examined learning effectiveness when matching the sequence of learning material according to the sequential-global learning style, with encouraging results [Bajraktarevic et al. 2003].

Mampadi et al. also state that adapting to learning style in general improves learning [Mampadi et al. 2011].

However, some studies concluded that adapting instruction based on learning style does not have a significant effect on learning outcome [Buch and Sena 2001; Siadaty and Taghiyareh 2007; Wolf 2007]. For example, Brown et al. conducted research that investigated learning style adaptivity, concluding that "it seems as though the use of a visual-verbal learning style model to provide matched or mismatched content to university students is unlikely to enhance learning in a statistically significant way" [Brown et al. 2006]. As to the opposite findings of related work, the studies took into account different learning style models, dimensions and sample sizes; the contexts in which they have been applied are also not the same as the present study.

This experiment contributes to current research on adaptivity by providing more evidence on learning effectiveness and on the importance of learning style in adaptive e-learning systems. Importantly, it is one of the few studies to examine carefully the effectiveness of adaptation based on the information perception dimension of learning style. This dimension has not been incorporated and evaluated as a single learner characteristic in an adaptive e-learning system. This adds to the originality of this research, because the AdaptLearn system is based on this dimension and this experiment revealed significant findings in terms of learning outcomes. The present study supports the view that matching learning objects to the information perception dimension of learning style significantly enhances learning outcomes, with a medium-to-large effect.

5.3.4.3 Learner Satisfaction

This section presents the results related to the hypothesis on learner satisfaction (H1.2). The matched group (*Mean* = 5.95, *SD* = 0.84, *Median* = 6.17) had larger mean and median scores than the mismatched group (*Mean* = 5.26, *SD* = 1.40, *Median* = 5.48), indicating that there was a positive effect on learner satisfaction when matching the sequence of learning objects to the information perception dimension of learning style. To determine if there is any significant difference in learner satisfaction between the matched group and the mismatched group, a statistical test was run using an alpha level (α) of 0.05. As data were not normally distributed, an independent sample Mann-Whitney U test was used. The results indicate that the general learner satisfaction score for the matched group (*Median* = 6.17) was significantly higher than the mismatched group (*Median* = 5.48), $U = 302.5$, $p = 0.02$, $r = 0.29$. H1.2 is therefore confirmed, and it can be concluded that matching the sequence of learning objects to the information perception dimension of learning style in the AdaptLearn system yields significantly better learner satisfaction than mismatching.

Learner satisfaction is one of the factors that is usually investigated in related work, and the vast majority of studies concerning learning style adaptation – irrespective of model or dimension type – conclude that adapting instruction based on learning style yields better learner satisfaction [Essalmi et al. 2010; Papanikolaou et al. 2003; Akbulut and Cardak 2012]. Popescu conducted a study with 64 students that examined learning style adaptation, with statistically significant findings when matching learning material to learning style compared to mismatching [Popescu 2010]. Filippidis and Tsoukalas also developed an adaptive e-learning system based on learning style and conducted an experiment with 62 students to evaluate it; the satisfaction results were significant [Filippidis and Tsoukalas 2009].

However, some studies that measured both learning outcome and learner satisfaction reported conflicting findings. Buch and Sena measured these two variables and concluded that adapting to learning style does not yield significantly better learning outcome but does enhance learner satisfaction [Buch and Sena 2001]. Nevertheless, the findings of this experiment support both variables and it can be concluded that matching learning objects to the information perception dimension of learning style in AdaptLearn significantly enhances learning outcome and learner satisfaction.

5.3.4.4 Additional Findings

A further analysis was conducted to test the difference between sensory and intuitive learners in terms of learning outcome. Figure 22 shows that sensory learners in the matched group had better learning outcome than intuitive learners in the same group. In the mismatched groups, sensory learners also had better learning outcome than intuitive learners. However, the matched group had greater learning outcome for both sensory and intuitive learners than the mismatched group. As a result, it is concluded that matching the sequence of learning material and the information perception style is beneficial for both types of learners.

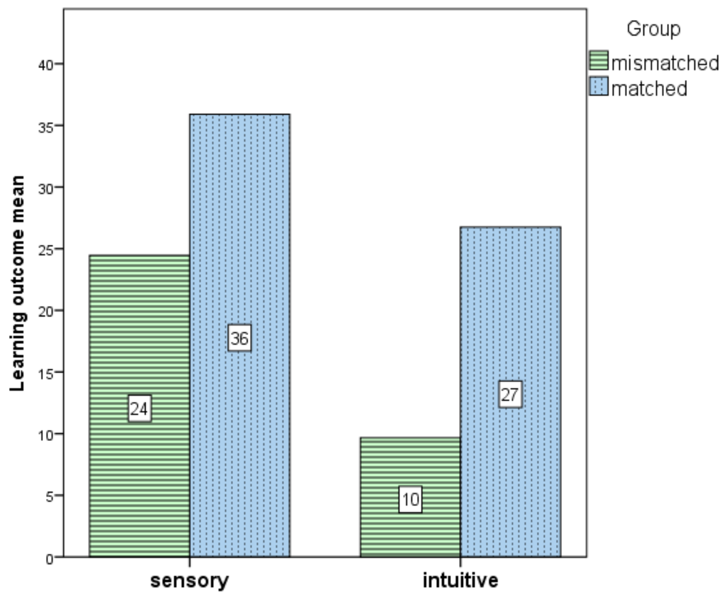


Figure 22. Learning outcome for sensory and intuitive learners.

With respect to the learning style characteristics, the learning outcome scores of the learners who have mild sensory and intuitive characteristics in both groups were approximately the same, as presented in Figure 23. It indicates that either matching or mismatching learning material to mild learning style preferences of learners may not lead to better learning outcomes. This raises the question of how an adaptive e-learning system can adapt and personalise learning material for learners according to their mild or neutral learning style preferences in order to enhance their learning.

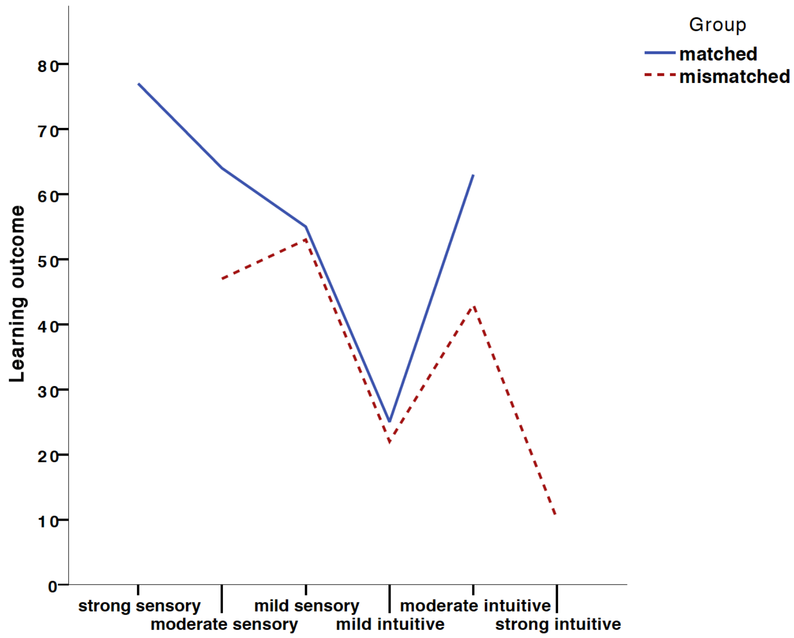


Figure 23. Learning outcome across the information perception dimension.

It was also observed that as the affinity of learners with learning style increases, the learning outcome for the matched group was higher than the mismatched group. For example, moderate sensory and intuitive learners in the matched group had better learning outcomes than moderate sensory and intuitive learners in the mismatched group. A comparison between learners who have a strong affinity with their learning style was not possible, as there were very few learners with strong characteristics in the experimental sample. A larger sample with balanced groups according to their affinity with learning style may thus be required. However, this type of experiment may demand more time to achieve balanced groups.

Concerning the time spent in seconds on learning, the matched group (*Mean* = 1054.79, *SD* = 493.21) and the mismatched group (*Mean* = 1002.03, *SD* = 361.69) had approximately the same average time spent on learning; this implies that either matching or mismatching the sequence of learning objects according to the information perception dimension of learning style did not lead to quicker learning. This finding was expected since the same learning objects were used for both groups, and all the participants had to complete all these learning objects. While the experiment was not designed primarily to investigate time spent, these results are observational findings from the experiment. Learning efficiency and faster learning variables can be taken into account in future experiments.

5.4 Experiment 2: Learning Style and Knowledge Level Adaptivity

5.4.1 Introduction

According to the results of Experiment 1, adapting instruction based on the information perception dimension of learning style yields better learning outcomes and learner satisfaction. However, other important learning factors should not be ignored [Ertmer and Newby 1993]. Tseng et al. report that there are few studies that examine the effect of combining two or more learner characteristics or sources in an adaptive e-learning system [Tseng et al. 2008]. Further customisation can be achieved by incorporating a combination of different learner characteristics such as knowledge level and learning style.

The AdaptLearn system can be configured to provide adaptation based on both the information perception dimension of learning style and knowledge level. The focus of this section is to evaluate the effectiveness of adaptation based on learning style and knowledge level, by conducting a controlled experiment. The experiment investigates three forms of adaptation. One takes into account the information perception dimension of learning style alone, another is based on knowledge level alone and the third involves the combination of the information perception dimension of learning style and knowledge level. The main research question being investigated in this experiment is:

RQ. How do learning outcome and learner satisfaction vary if an adaptive e-learning system is based on the following learner characteristics:

- The information perception dimension of learning style alone;
- The knowledge level alone;
- A combination of the two characteristics?

5.4.2 Hypotheses

Learning outcome and learner satisfaction are the main variables taken into account in this experiment, but there are two types of learning outcome in the hypotheses below. First, learning outcome (immediate) is measured using a pre-test and an *immediate* post-test taken right after interacting with the system to study a set of lessons in this experiment. Second, learning outcome (delayed) is measured using a pre-test and a *delayed* post-test (follow-up test) taken by participants after a passage of time after completing the experiments to measure the sustained knowledge.

In this experiment, two learner characteristics are taken into account: the information perception dimension of learning style (LS) and knowledge level (K). The combination of the two learner characteristics is referred to as LS+K.

For this experiment, six hypotheses were put forward:

H2.1: Adaptation based on LS+K yields significantly better *learning outcomes* (immediate) than adaptation based on K alone.

H2.2: Adaptation based on LS+K yields significantly better *learning outcomes* (delayed) than adaptation based on K alone.

H2.3: Adaptation based on LS+K yields significantly better *learning outcomes* (immediate) than adaptation based on LS alone.

H2.4: Adaptation based on LS+K yields significantly better *learning outcomes* (delayed) than adaptation based on LS alone.

H2.5: Adaptation based on LS+K yields significantly better *learner satisfaction* than adaptation based on K alone.

H2.6: Adaptation based on LS+K yields significantly better *learner satisfaction* than adaptation based on LS alone.

According to these hypotheses, three experimental conditions or groups were established.

- **LS**: A group of participants that interacts with a version of AdaptLearn that adapts learning material based on the information perception dimension of learning style (LS) alone.
- **K**: A group of participants that interacts with a version of AdaptLearn that adapts learning material based on knowledge level (K) alone.
- **LS+K**: A group of participants that interacts with a version of AdaptLearn that adapts learning material according to the combination of LS and K.

The description of how AdaptLearn provides adaptation based on these characteristics can be found in Chapter 4. Participants in all the experimental groups experienced the same interface layout, and the same learning material was used for all groups in the experiment. The difference between the groups is the form of adaptation provided by AdaptLearn. It should be noted that the system might recommend some additional learning material to be studied by learners in a specific group because of its adaptive nature. This may affect the treatment of the experimental groups. However, the additional material does not largely differ from the main learning material; they both have the same learning objectives. The dependent variables measured in this experiment are learning outcomes (immediate and delayed) and learner satisfaction. The instruments used to measure the information perception style of participants and the dependent variables are described in Section 5.2.3.

5.4.3 Procedure

The experiment was conducted through twelve main experimental sessions, lasting 85–120 minutes at the University of Hail, Saudi Arabia. In each session, the participants were introduced to the main objectives of the experiment and informed of the procedure. They were asked to access the AdaptLearn system through an Internet browser. They completed a demographic data form and the Index of Learning Style questionnaire using the system. Then, the system assigned participants to experimental groups (LS, K or LS+K) and directed them to complete a pre-test. The next step involved the study by participants of learning material on computer security, the application domain of the system. At the end of the learning session, they immediately completed a post-test, followed by the learner satisfaction questionnaire. Two to three weeks later, the same participants completed a follow-up test.

5.4.4 Results and Discussion

5.4.4.1 Introduction

The experiment was conducted with 174 participants, 102 males (58.6%) and 72 females (41.4%). They were all undergraduate students in a computer science degree programme. The mean age of the participants was 21.07 (SD = 1.48), the maximum age was 25 and the minimum age was 19. All three experimental conditions (LS, K, LS+K) were balanced in terms of group size, with 58 participants each and gender (34 males and 24 females). The experiment was balanced and controlled to allow for more useful comparisons between the experimental groups.

With regard to the distribution of participants in the information perception dimension, there were more sensory learners (70.68%) than intuitive learners (29.31%). The majority of the participants had mild to moderate learning style characteristic, and very few participants had a strong characteristic in either the sensory and intuitive categories. Figure 24 presents the percentages of participants in the sub-categories (mild, moderate and strong) of the information perception dimension.

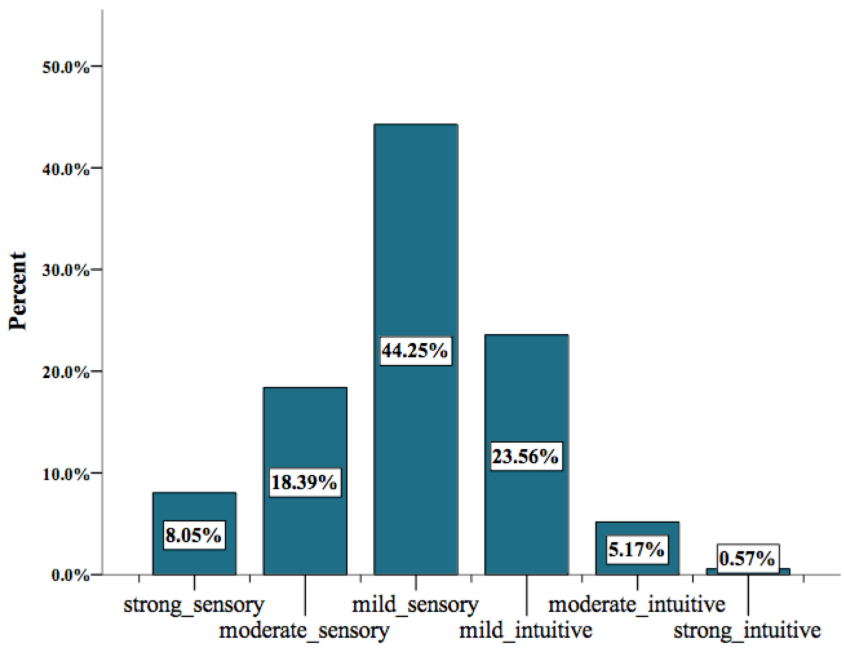


Figure 24. Experiment 2: Distribution of participants in the information perception dimension.

5.4.4.2 Learning Outcome

The four hypotheses (H2.1, H2.2, H2.3 and H2.4) concerning both immediate and delayed learning outcome were tested. Table 10 presents the results of the mean, standard deviation and one-way ANOVA measuring the variables: pre-test, post-test, follow-up test, $LearningOutcome_{immediate}$ and $LearningOutcome_{delayed}$ for each experimental group (LS, K and LS+K). Concerning prior knowledge measured by pre-test, all the experimental groups had approximately the same mean results with no statistical difference.

Table 10. Mean, standard deviation (SD), partial eta squared (η_p^2) and the results of one-way ANOVA relating to the experimental groups (LS, K and LS+K) measuring a number of variables. *$p < 0.0005$.

Variable/group		LS	K	LS+K
Pre-test	Mean (SD)	5.97(8.64)	7.41 (10.19)	6.53 (8.07)
	F(2,171)	0.38		
	p	0.68		
Post-test	Mean (SD)	59.47 (17.05)	72.16 (14.90)	82.02 (13.35)
	F(2,171)	32.17		
	p	0.000*		
	η_p2	0.27		
Follow-up test	Mean (SD)	35.52 (16.27)	54.59 (14.58)	72.43 (14.26)
	F(2,171)	87.05		
	p	0.000*		
	η_p2	0.51		
$LearningOutcome_{immediate}$	Mean (SD)	53.50 (18.92)	64.74 (18.94)	75.48 (14.18)
	F(2,171)	22.89		
	p	0.000*		
	η_p2	0.21		
$LearningOutcome_{delayed}$	Mean (SD)	24.55 (16.61)	47.17 (18.68)	65.90 (14.43)
	F(2,171)	68.96		
	p	0.000*		
	η_p2	0.45		

As to the post-test, the LS+K group had the largest mean results followed by the K group and the LS group (LS+K > K > LS). In addition, there exists statistically significant differences between these groups. This case is similar to the results of the follow-up test but with different mean values for each group. Statistically significant findings were also observed indicating that both $LearningOutcome_{immediate}$ and $LearningOutcome_{delayed}$ for the LS+K group were greater than the K group and the LS group. It was also observed that the K group had greater mean results than the LS group.

The one-way ANOVA test indicated significant differences between the three experimental groups. The results of this test did not show exactly where the significance between each two experimental groups lies. As further analysis is needed to compare the experimental groups pairwise and determine which groups in the sample differ, a Tukey post hoc test was also run. Figure 25 summarises these results, showing that in all the comparisons between each pair of experimental groups there were statistically significant differences, except the results related to the pre-test variable. For example, there was a statistically significant difference for the post-test between the LS+K and K groups, $p = 0.002$; between the LS+K and LS groups, $p = 0.000$ (<0.0005); and between the K and LS groups, $p = 0.000$ (<0.0005).

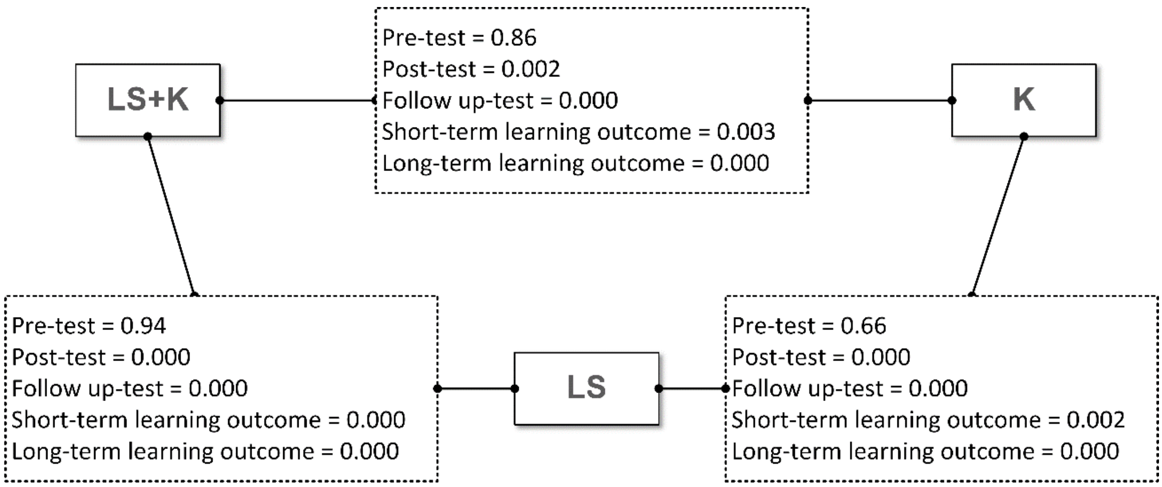


Figure 25. The results of a Tukey post hoc test measuring a number of variables to compare each pair of experimental groups. The values indicate the significance level (*p* value).

The post-test, follow-up test, $\text{LearningOutcome}_{\text{immediate}}$ and $\text{LearningOutcome}_{\text{delayed}}$ results for the LS+K group were thus the largest, followed by the K group, then the LS group. One exception is that there was no statistically significant difference between all the experimental variables (LS, K and LS+K) in terms of the pre-test. These results imply that the participants in the experimental groups had the same prior knowledge. This particular finding allowed for more useful comparisons between the experimental groups by eliminating the effect of any prior knowledge as a confounding factor.

Based on the findings, the four hypotheses (H2.1, H2.2, H2.3 and H2.4) related to learning outcome are therefore confirmed as follows:

- Adaptation based on LS+K yields significantly better *learning outcomes* (immediate) than adaptation based on K alone.
- Adaptation based on LS+K yields significantly better *learning outcomes* (delayed) than adaptation based on K alone.
- Adaptation based on LS+K yields significantly better *learning outcomes* (immediate) than adaptation based on LS alone.
- Adaptation based on LS+K yields significantly better *learning outcomes* (delayed) than adaptation based on LS alone.

Since several related studies report that learning outcome results vary [Brown et al. 2009; Buch and Sena 2001], the findings of this experiment relate mainly to those reporting significant learning outcome findings and to those which take into account both learning style and knowledge level [Buch and Sena 2001; Limongelli et al. 2009; Akbulut and Cardak 2012; Truong 2016]. Tseng et al. designed an adaptive e-learning system based on two characteristics (learning style and learning behaviours), and carried out an experiment that compared three versions of the system: two versions that incorporated a single characteristic and a third that integrated a combination of the two characteristics to determine how they vary in terms of learning effectiveness [Tseng et al. 2008]. They concluded that an adaptive e-learning system based on the two learner characteristics is more helpful to learners in enhancing learning outcome than a system based on a single characteristic.

Peña et al. also developed a system based on learning style and learner knowledge, conducting an experiment with five teachers and 25 students; the results were related to the acceptance of adaptivity in the form of charts [Peña et al. 2002]. However, they did not take into account any statistical testing for either learning effectiveness or learner satisfaction as important factors for success, given their small sample size. In contrast, Limongelli et al. took a more careful approach in evaluating an adaptive e-learning system and produced encouraging results in terms of learning outcomes [Limongelli et al. 2009]. However, their experiment was also conducted with a small sample of only 30 participants.

Experiment 2 in the present study differs from previous work in investigating two learner characteristics that are uniquely related to AdaptLearn: the information perception learning style and knowledge level. This study is also distinctive in conducting a carefully designed and controlled experiment with a reasonably large number of participants. The main limitations of the majority of related studies stem from a lack of careful design and execution of experiments and from very small sample sizes [Akbulut and Cardak 2012; Truong 2016; Chin 2001; Brown et al. 2009]; these issues were addressed in this experiment.

The findings of this experiment are associated not only with learning outcomes measured using a pre-test and an immediate post-test but also on learning outcomes measured using a delayed post-test. Both types of learning outcome were higher when incorporating learning style and knowledge level as learner characteristics in AdaptLearn than when incorporating only one single learner characteristic. Very few related studies concerning adaptive e-learning systems report on findings related to the two types of learning outcome (immediate and delayed), thus adding more value to this study [Brown et al. 2009; Akbulut and Cardak 2012; Limongelli et al. 2009; Truong 2016].

This experiment is in line with Experiment 1; it also contributes to current research on adaptivity by providing more evidence on learning outcomes and on the importance of incorporating learner knowledge and learning style as learner characteristics in adaptive e-learning systems. It is argued in this work that adaptation based on the combination of the information perception dimension of learning style and knowledge level significantly enhances learning outcome.

5.4.4.3 Learner Satisfaction

This section presents the results related to the learner satisfaction hypotheses (H2.5 and H2.6). Table 11 shows that the LS+K group had the largest mean and median scores followed by the K group, then the LS group. However, the LS+K group and the K group had nearly the same median scores. These findings generally indicate that adaptation based on the combination of the information perception dimension of learning style and knowledge level leads to higher levels of satisfaction than adaptation based on a single learner characteristic. To confirm hypotheses H2.5 and H2.6 fully, it is essential to investigate the significance of the differences between the experimental groups.

Table 11. Satisfaction scores for the experimental groups.

Group	N	Mean	SD	Median
LS	58	5.15	1.23	5.29
K	58	5.70	1.24	6.14
LS+K	58	5.88	1.14	6.15

As data related to the satisfaction variable is not normally distributed, Mann-Whitney U tests were run using an alpha level (α) of 0.05 to compare groups pairwise and determine if there was any statistical difference in satisfaction scores between each pair of experimental groups. An investigation between the satisfaction scores of the LS+K group and the scores of the K group showed no statistically significant difference, U = 1540.5, p = 0.43, r = 0.01. The results thus indicate that hypothesis H2.5 is not supported; adaptation based on LS+K did not yield significantly better learner satisfaction than adaptation based on K alone. It was also observed that there was a statistically significant difference between the K group and the LS group, U = 1188, p = 0.006, r = 0.21. Giving these findings, learners may perceive that the system meets their knowledge levels in the condition of LS+K and the condition of K, whereas learning style may be perceived as an additional or complementary factor to knowledge level. However, this is not the case when taking into account learning outcome as supported by the confirmation of the hypotheses H2.1 and H2.2.

Comparing the LS+K group and the LS group showed a statistically significant difference, U = 1044, p = 0.000 (<0.0005), r = 0.27. Hypothesis H2.6 is therefore confirmed, indicating that adaptation based on LS+K yields significantly better learner satisfaction than adaptation based on LS alone.

These results confirm that participants who interacted with the version of AdaptLearn based on the combination of learning style and knowledge level had better satisfaction scores than those who interacted with the version of AdaptLearn that adapts according to learning style alone. However, there was no significant difference in satisfaction when adapting according to the combination of learning style and knowledge level as opposed to knowledge level alone. This suggests that knowledge level should be taken into account as a primary learner characteristic regardless of the learning style of learners. Incorporating learning style may lead to further enhancement in learning outcome, as reported in the previous section. A higher level of satisfaction may lead learners to be more motivated and engaged with the learning process, so that their learning outcome will be improved [Shee and Wang 2008; Sun et al. 2008; Wang 2003].

5.4.4.4 Additional Findings

The time spent in seconds on learning for the three experimental groups was computed and is presented in Table 12. The LS group spent the least time on learning, followed by the K group, then the LS+K group. Since the LS+K group had the longest time spent on learning, the participants of this group may have studied more additional learning material than any other group. However, the differences between the experimental groups were small.

Table 12. Time spent results for the experimental groups.

Group	N	Mean	SD	Min.	Max.	F(2, 171)	Sig.
LS	58	2226.33	519.98	1032	3396	1.93	0.15
K	58	2376.14	655.15	1057	4037		
LS+K	58	2478.72	711.13	1011	4438		

To investigate if there was any significant difference between these groups, a one-way ANOVA test was run using an alpha level (α) of 0.05. The results indicate no statistically significant difference between the three groups, suggesting that there could be no specific form of adaptation that leads to learning more quickly. As with Experiment 1, this experiment was not primarily designed either to investigate or decrease the time spent on learning. These results can be considered as non-conclusive observations from the experiment.

5.5 Experiment 3: Perceived Usability

5.5.1 Introduction

Usability is an issue that demands investigation since an adaptive system may be effective in enhancing learning but can also be difficult to use and vice versa [Gena 2005; Höök 2000]. Ardito et al. point out that there is a requirement for a better understanding of where adaptivity in e-learning systems is beneficial and where it is harmful [Ardito et al. 2006]. Zaharias and Poylymenakou state that “very little has been done to critically examine the usability of e-learning applications” [Zaharias and Poylymenakou 2009]. As a result, a third controlled experiment was designed to investigate the effect of adaptation generated by AdaptLearn in terms of its perceived level of usability and to examine the relationship between usability and learning outcome [Alshammari et al. 2015b; Alshammari et al. 2016].

Two research questions are investigated in this experiment:

RQ1. Do adaptive e-learning systems based on the information perception dimension of learning style and knowledge level yield higher levels of perceived usability than non-adaptive systems?

RQ2. Is there a relationship between perceived usability levels and learning outcomes in adaptive e-learning systems and non-adaptive systems?

5.5.2 Hypotheses

For this experiment, two main hypotheses were put forward:

H3.1: An adaptive e-learning system based on the combination of the information perception dimension of learning style and knowledge level yields significantly higher levels of *perceived usability* than a non-adaptive e-learning system.

H3.2: There is a positive correlation between *learning outcome* and *perceived level of usability* when using an adaptive e-learning system.

According to these hypotheses, two experimental conditions were proposed, an adaptive condition and a non-adaptive condition. In the former, participants interacted with a version of AdaptLearn, which adapts learning material according to the information perception dimension of learning style and knowledge level. In the non-adaptive condition, participants interacted with the same system but without the feature of adaptivity.

The main dependent variable measured in this experiment is the perceived level of usability. Learning outcome are also measured in order to investigate their relationship with perceived levels of usability. The instruments used to identify the information perception style of participants and to measure the dependent variables are described above (see Section 5.2.3).

5.5.3 Procedure

The experiment was conducted through eight experimental sessions of about 85–110 minutes at the University of the Gambia. Participants were informed of the experimental procedure. They were asked to access the AdaptLearn system through an Internet browser and completed a demographic data form and the ILS questionnaire using the system. Then, the system randomly assigned participants to the adaptive group or the non-adaptive group and directed them to complete a pre-test. The next step involved the study by participants of learning material on computer security, the application domain of the system. When completing each learning unit, a post-test was provided by the system to learners, so that the scores of these tests could be used to measure learning outcomes at the end of the interaction with the system. At the end of the learning session participants completed a usability questionnaire.

5.5.4 Results and Discussion

5.5.4.1 Introduction

The experiment was conducted with 75 participants, 43 males (57.3%) and 32 females (42.7%). The adaptive group involved 39 participants whereas the non-adaptive group had 36 participants. The participants were undergraduate students in a computer science degree programme. The mean age of the participants was 22.21 (SD = 3.13), the maximum age was 36 and the minimum age was 19.

In terms of learning style, there were more sensory learners (64%) than intuitive learners (36%). The majority of participants had mild to moderate learning style characteristics, with very few showing strong characteristics for either sensory or intuitive categories. Figure 26 presents the percentages of participants in the sub-categories (mild, moderate and strong) of the information perception dimension.

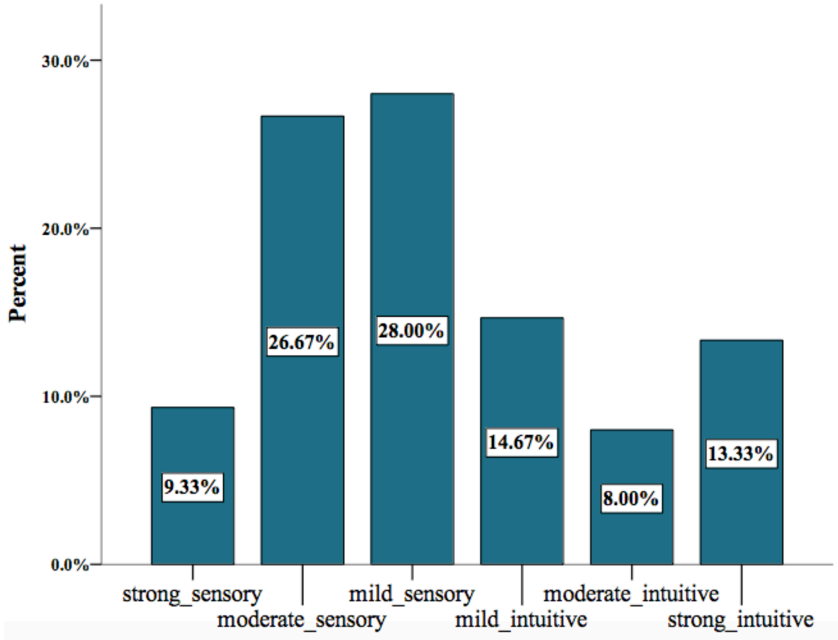


Figure 26. Experiment 3: Distribution of participants in the information perception dimension.

5.5.4.2 Usability

Hypothesis H3.1 concerning the perceived usability level of AdaptLearn was tested. The usability scores for the adaptive version (*Mean* = 79.46, *SD* = 13.14) and the non-adaptive system (*Mean* = 71, *SD* = 13.67) were acceptable, as their average score is larger than 70 [Bangor et al. 2008]. This may imply that both systems are useful and valuable in learning, and the learners were generally satisfied and found them easy to use.

In related work, Shi et al. recently developed an adaptive social e-learning system called Topolor and examined its usability using the same tool as employed in this experiment; the overall average score of usability was 75.75 [Shi et al. 2013]. Cristea et al. also compared three different adaptive e-learning systems using the same tool called MOT, WHURLE and MOT2WHURLE; their usability scores were 75, 66.6 and 60.7, respectively [Cristea et al. 2005]. The evaluation of usability of the AdaptLearn system yields better results than the evaluation of usability of those systems as it scored 79.46, as measured by a controlled experiment designed primarily to investigate usability.

In this experiment, the two versions (adaptive and non-adaptive) were also compared to obtain a deeper insight into their usability and whether the provision of adaptivity has any significant impact on usability. As there was homogeneity of variance between the study groups as assessed by Levene's test for equality of variances, $F = 0.07$, $p = 0.79$ and that the data were normally distributed, an independent sample *t*-test was conducted to compare the two conditions using an alpha level (α) of 0.01. It was found that there was a statistically significant difference between the general usability score of the two systems, $t(73) = 2.73$, $p = 0.008$, $d = 0.63$. The effect size was between medium and large. H3.1 is therefore confirmed; it can be inferred that the adaptive e-learning system based on a combination of the information perception dimension of learning style and knowledge level yields significantly higher levels of perceived usability than a non-adaptive e-learning system.

Although both systems had the same interface layout, significant results related to the perceived usability of the adaptive version were generated; adaptivity in e-learning systems enhances the perceived level of general usability. The high level of perceived usability may lead learners to feel more satisfied, engaged and motivated to use the adaptive e-learning system [Ardito et al. 2006; Zaharias and Poylymenakou 2009]. It may thus be the case that highly usable adaptive e-learning systems improve learning and lead learners to focus on their learning tasks rather than system functionality [Orfanou et al. 2015].

In an investigation of the results related to each item of the System Usability Scale tool, there were significant findings related to two items, whereas the findings of other items were not statistically significant. In response to the item “I think I would like to use this website frequently”, the most significant difference is that participants would use the adaptive version (*Mean* = 4.62, *SD* = 0.63) more frequently than the non-adaptive system (*Mean* = 3.89, *SD* = 1.06), $t(73) = 3.628$, $p = 0.001$. This is a key point in terms of the usability of systems, which may provide a justification for the adaptivity and recommendation mechanisms provided by the adaptive version. Adaptivity may influence learners to perceive that the system would help them when needed and provide them with dynamic support according to their knowledge and preferences. The recommendations of the adaptive system may also enhance their intellectual curiosity, satisfaction and engagement. In contrast, learners may find the non-adaptive system rigid and unresponsive to their needs; they may thus be less likely to use the non-adaptive version as a tool for learning.

In relation to the item "I thought this website was easy to use", participants find the adaptive system (*Mean* = 4.15, *SD* = 1.15) easier to use than the non-adaptive system (*Mean* = 3.39, *SD* = 1.31), $t(73) = 2.676$, $p = 0.009$. This is a noteworthy finding on the complexity of adaptivity, as it may increase the cognitive load of the learner trying to understand the adaptive system's functionality when their main focus should be on the learning process. It may however be expected that using adaptive systems would not be substantially easier than using traditional or non-adaptive systems. Learners may find it more helpful and easier to use a system which provides personalised feedback and recommendations based on their interaction with the system to meet their needs. In the case of AdaptLearn, it recommends what learners should do if things go wrong and what to do next or it reports on the current state of the learning process. It may be the case that once learners gain an appreciation of the adaptive system, they may find it easier to use and more useful.

5.5.4.3 Learning Outcome

Learning outcome was also measured in this experiment. It was generally found that participants who used the adaptive system of AdaptLearn had higher learning outcome scores (*Mean* = 86, *SD* = 17.20) than participants who used the non-adaptive system (*Mean* = 65.03, *SD* = 19.85). As there was homogeneity of variance between the study groups as assessed by

Levene's test for equality of variances, F = 1.37, p = 0.24 and as data were normally distributed, an independent sample t-test was also run using an alpha level (α) of 0.01. There was a statistically significant difference between learning outcome scores of the adaptive system and the non-adaptive system with a large effect size, $t(73) = 4.90$, $p = 0.000$ (<0.0005), $d = 1.13$. This finding is expected since it was also supported and confirmed in Experiment 1 and Experiment 2.

This finding relates to immediate learning outcome, as participants immediately completed post-tests provided at the end of each lesson. Although measuring learning outcomes was not the main goal of the experiment, the results in that area may help shed light on its relationship with the perceived level of usability.

5.5.4.4 Usability and Learning Outcomes

This section is concerned with hypothesis H3.2, which refers to the relationship between the perceived level of usability and learning outcome for the adaptive group and non-adaptive group. Since data were normally distributed, Pearson correlation coefficient tests were run. Concerning the group of participants who interacted with the adaptive system (adaptive condition), there was a positive but weak and not statistically significant correlation between the perceived level of usability and learning outcome, $r(37) = 0.19$, $p = 0.26$. As to the group of participants who interacted with the non-adaptive system (non-adaptive condition), there was either no or only very weak correlation between the perceived level of usability and learning outcome, $r(34) = 0.035$, $p = 0.84$. According to these findings, H3.2 is not confirmed; it can be stated that there is no positive or strong correlation that is statistically significant between learning outcome and perceived usability levels for the adaptive group compared to the correlation for the non-adaptive group. However, the correlation found for the adaptive group is still better than the correlation for the non-adaptive group.

5.6 Conclusion

This chapter was concerned with the evaluation of different forms of adaptation that are generated by AdaptLearn in terms of learning effectiveness, learner satisfaction and perceived level of usability. This evaluation employed the method of experimental evaluation, using controlled experiments with participants in a realistic learning environment. This is highly relevant to this research and has been suggested as an appropriate approach for evaluating adaptive e-learning systems [Chin 2001; Brown et al. 2009; Pashler et al. 2008; Paramythis et al. 2010; Akbulut and Cardak 2012; Truong 2016]. Rigorous experimental design, careful investigation and precise reporting of results were taken into account in all the experiments. This contrasts with related work that, with minor exceptions, lacks carefully designed experiments or uses small sample sizes [Akbulut and Cardak 2012; Truong 2016; Brown et al. 2009; Wolf 2007; Özyurt and Özyurt 2015].

In this study, three experiments were conducted, each with specific objectives and hypotheses. Experiment 1 was concerned with the effect of adaptation based on the information perception dimension of learning style. Personalised sequences of learning objects were provided to each learner. The findings indicated that matching the sequence of learning objects to the information perception dimension of learning style in AdaptLearn yields significantly better learning outcome and learner satisfaction compared to non-matching sequences. The time spent on learning for the matched group and the mismatched group was approximately the same because participants in both groups studied the same learning material but with different sequences.

Experiment 2 investigated the learning effectiveness of three forms of adaptation: one based on the information perception dimension of learning style alone, one based on knowledge level alone and a third based on the combination of the information perception dimension of learning style and knowledge level. The findings indicated that adaptation based on the combination of the information perception dimension of learning style and knowledge level yields significantly better learning outcome and learner satisfaction than adaptation based on a single learner characteristic, being knowledge level or learning style.

Experiment 3 investigated the level of perceived usability when providing adaptation by AdaptLearn and the relationship between usability and learning outcomes. Adaptive e-learning systems based on the combination of the information perception dimension of learning style and knowledge level yield significantly higher levels of perceived usability compared to non-adaptive e-learning systems. However, although there was a positive relationship between the perceived level of usability and learning outcomes, it was weak and non-significant. This finding related to the group of participants who interacted with the adaptive system in this experiment. There was no relationship between the perceived level of usability and learning outcome considering the group of participants who interacted with the non-adaptive system.

Some points regarding the originality, contribution and possible limitations of the present study should be highlighted. The findings clearly shed more light on the information perception dimension of the Felder-Silverman learning style model, and the experiments are among the few that deal directly with this dimension, either as a single learner characteristic or in combination with knowledge level.

Importantly, the findings cannot be generalised to other learning style dimensions and other learning style models. They are closely linked to the information perception or sensory-intuitive dimension of learning style based on the Felder-Silverman learning style model and the proposed adaptive approach provided by the AdaptLearn system. However, this dimension, as noted above, is related to dimensions in other learning style models such as the Kolb model [Kolb 1984] and MBTI [Myers and McCaulley 1985]. Although this dimension is recognised as the most important learning style dimension [Felder et al. 2002; McCaulley 1990], other dimensions may also be incorporated in the proposed approach to investigate their effect on learning. The visual-verbal dimension has been researched extensively and has been shown not to yield significant enhancement in learning [Mayer and Massa 2003; Massa and Mayer 2006; Brown et al. 2006; Kollöffel 2012]. The active-reflective dimension can be supported implicitly by systems when they incorporate collaborative and interactive learning features [Jeong and Lee 2008; Zhan et al. 2011]. The sequential-global dimension seems not to support learning significantly if it is applied in e-learning systems, and it may relate to the design of system interfaces [Brown et al. 2009].

Taking into account the information perception dimension in particular has the merit of offering a resolution to the ongoing debate in teaching between the exclusive application of either an abstract-to-concrete approach or a concrete-to-abstract approach. It provides a compromise by adopting an appropriate approach that takes into account the learning style of each learner based on the information perception dimension of learning style. It is evident, based on the findings, that meeting learners' preferences is necessary for optimal learning and satisfaction. However, a more refined approach should have been used for a better fit with the sub-categories of the information perception dimension of learning style. For example, it may be more effective to treat learners differently according to their particular affinity with the mild, moderate or strong characteristics of a particular learning style.

It should be noted that although the participants in the three experiments were different, the distribution of the participants in the information perception dimension (sensory to intuitive) was approximately similar. There were far more sensory learners than intuitive learners, and the majority of both had mild to moderate characteristics. Only very few learners had strong characteristics. This finding largely agrees with several other related studies [Graf et al. 2007; Zywno 2003; Felder and Spurlin 2005]. Therefore, balanced numbers of participants across the sub-categories of this dimension may take more time to achieve to conduct a more useful comparison.

The results of the experiments offer more evidence for the importance of personalisation and adaptation of learning material and their sequencing to meet the different needs of learners in e-learning systems. The results are mainly related to the two characteristics integrated in the learner model of AdaptLearn, the information perception style and knowledge level. Another important point is that the experiments were conducted with undergraduate students studying in a computer science programme. Since the adaptive approach provided by AdaptLearn may be applicable and beneficial in different contexts and domains, more research is needed that takes into account diverse students who study different subjects at different levels. More detailed suggestions for future work are also offered in the next chapter.

Chapter 6. Conclusion

6.1 Introduction

This chapter summarises the work carried out in this research, with the research questions addressed and the findings of the experimental evaluation discussed. An outline of the contributions of this study is given followed by a review of its limitations. Finally, future avenues for this research are laid out.

6.2 Summary of the Work

This study began in Chapters 2 and 3 by analysing the existing literature to demonstrate the need for this work; a number of research issues and gaps were identified.

An adaptive e-learning framework was initially proposed by taking into account frameworks and models in relevant published research. It contains the major components that are required to produce adaptation including the domain model, the learner model and the adaptation model. Within the proposed framework, an adaptive e-learning system called AdaptLearn was designed and implemented. The AdaptLearn system can provide adaptation based on the information perception dimension of learning style and knowledge level. The system can be configured to alternate between different forms of adaptation; adaptation can be based on learning style alone, knowledge level alone or can be based on a combination of learning style and knowledge level. AdaptLearn constructs personalised learning paths and provides adaptive guidance to learners as adaptive methods to enhance learning. Chapter 4 details the proposed framework and describes AdaptLearn.

Three carefully designed and conducted controlled experiments were carried out to evaluate the different forms of adaptation that are generated by the AdaptLearn system. Experiment 1 investigated the effectiveness of adaptation based on learning style in terms of learning outcomes and learner satisfaction. Experiment 2 investigated how learning outcomes and learner satisfaction vary when AdaptLearn provides adaptation based on learning style alone, knowledge level alone and a combination of the two. Experiment 3 was also carried out to evaluate the perceived usability level and its relationship with learning outcomes. The findings of these experiments were reported in Chapter 5 and are summarised in the next section.

6.3 Research Questions Re-visited

Four research questions were put forward. The work carried out to address each research question and the findings are discussed below.

Research Question 1. Does adaptation based on the information perception dimension of learning style enhance learning and does it lead to a high level of learner satisfaction?

To answer this question, Experiment 1 was conducted with 60 participants (see Section 5.3). This experiment investigated whether matching the sequence of learning objects to the information perception dimension of learning style enhances learning outcome and learner satisfaction when compared to a mismatched sequence. The findings indicated that matching the sequence of learning objects to the information perception dimension of learning style in AdaptLearn yields significantly better learning outcome and learner satisfaction than non-matching sequences with a medium-to-large effect size.

The findings of the present study support the notion that adapting to learning style can be effective [Limongelli et al. 2009; Akbulut and Cardak 2012]. However, some studies have arrived at the conclusion that adapting instruction based on learning style does not have a significant effect on learning outcome (see Section 5.3.4.2) [Buch and Sena 2001; Siadaty and Taghiyareh 2007; Brown et al. 2007; Wolf 2007]. In related studies with opposite findings, different learning style models, dimensions and sample sizes were employed. The contexts in which they were applied are also unlike those in Experiment 1. This experiment thus contributes to current research on adaptivity by providing more evidence on learning effectiveness and on the importance of learning style in adaptive e-learning systems. Importantly, it is one of the few studies to examine carefully the effectiveness of adaptation based on the information perception dimension of learning style, which had not previously been incorporated and evaluated as a single learner characteristic in an adaptive e-learning system.

Learner satisfaction has been investigated frequently in related work, with the vast majority of studies concerning learning style adaptivity – irrespective of model or dimension type – concluding that adapting instruction based on learning style yields better learner satisfaction [Essalmi et al. 2010; Papanikolaou et al. 2003; Akbulut and Cardak 2012]. However, some studies that measured both learning outcome and learner satisfaction reported conflicting findings [Essalmi et al. 2015]. For example, Buch and Sena measured these two variables and concluded that adapting to learning style does not yield significantly better learning outcome but does enhance learner satisfaction [Buch and Sena 2001]. Nevertheless, from the findings of Experiment 1, it can be concluded that matching the sequence of learning objects to the information perception dimension of learning style in AdaptLearn significantly enhances both learning outcome and learner satisfaction.

Research Question 2. How do learning outcome and learner satisfaction vary if an adaptive e-learning system is based on the following learner characteristics:

- The information perception dimension of learning style alone;
- Knowledge level alone;
- A combination of the two characteristics?

To answer this question, Experiment 2 was carried out with 174 participants to determine the learning effectiveness of three forms of adaptation (see Section 5.4). One takes into account the information perception dimension of learning style alone, another is based on knowledge level alone and the third involves a combination of the two. The findings indicated that adaptation based on the combination of the information perception dimension of learning style and knowledge level yields significantly better learning outcome and learner satisfaction than adaptation based on either single learner characteristic.

Since several related studies report that learning outcome results vary [Brown et al. 2009; Buch and Sena 2001], the findings of this experiment relate primarily to those reporting significant learning outcome findings and to those which take into account both learning style and knowledge level (see Section 5.4.4) [Buch and Sena 2001; Limongelli et al. 2009; Akbulut and Cardak 2012; Truong 2016]. The present study is distinguished from published research in investigating two learner characteristics that are uniquely related to AdaptLearn: the information perception learning style and knowledge level. This study is also distinctive in conducting a carefully designed and controlled experiment with a reasonably large number of participants. The main limitations of the majority of related studies stem from a lack of careful design and execution of experiments and from very small sample sizes; these issues were avoided in Experiment 2 of the present study [Akbulut and Cardak 2012; Truong 2016; Chin 2001; Brown et al. 2009].

Furthermore, the findings are associated not only with learning outcomes measured using a pre-test and an immediate post-test but also on learning outcomes measured using a delayed post-test (follow-up test) to examine the sustained knowledge. Both types of learning outcome were higher when incorporating learning style and knowledge level as learner characteristics in AdaptLearn than when incorporating a single learner characteristic. Very few related studies concerning adaptive e-learning systems report on findings related to the two types of learning outcome (immediate and delayed) [Brown et al. 2009; Akbulut and Cardak 2012; Limongelli et al. 2009; Truong 2016], thus adding more value to this study.

Research Question 3. Do adaptive e-learning systems based on the information perception dimension of learning style and knowledge level yield higher levels of perceived usability than non-adaptive systems?

To answer this question, Experiment 3 was performed with 75 participants to investigate the effect of adaptation in terms of the perceived level of usability and to examine the relationship between usability and learning outcomes (see Section 5.5). The experiment compared the AdaptLearn system taking into account learning style and knowledge level with a version of the same system but without the feature of adaptivity. The experiment's findings revealed that adaptive e-learning systems based on the combination of the information perception dimension of learning style and knowledge level yield significantly higher levels of perceived usability compared to non-adaptive e-learning systems.

The usability of AdaptLearn, based on the findings of Experiment 3, appears to be better than the usability of a number of systems that have been reviewed (see Section 5.5.4.2); it also has the advantage of being measured by a controlled experiment designed primarily to investigate usability. Based on the findings, it can be concluded that the adaptive e-learning system based on a combination of the information perception dimension of learning style and knowledge level yields significantly higher levels of perceived usability than a non-adaptive e-learning system. Adaptivity may influence learners to believe that the system would support them dynamically in accordance with their knowledge and preferences. Learners may also find that an adaptive system which provides personalised feedback and recommendations based on their interaction with the system is easier to use. The recommendations of the adaptive system may also heighten their intellectual curiosity and improve satisfaction and engagement. It may be the case that once learners gain a deeper appreciation of the adaptive system, they may find it more useful. In contrast, learners may find the non-adaptive system rigid and unresponsive to their needs; they may thus be less likely to use the non-adaptive version as a tool for learning.

Research Question 4. Is there a relationship between perceived usability level and learning outcomes in adaptive e-learning systems and non-adaptive systems?

Experiment 3 was also designed to answer this question. The relationship between perceived usability and learning outcomes in adaptive e-learning systems is rarely taken into account, so that was investigated in this research [Alshammari et al. 2015b; Alshammari et al. 2016]. The findings showed a positive relationship between the perceived level of usability and learning outcomes, but it was weak and non-significant. This finding is related to the group of participants who interacted with the adaptive system in this experiment. For the group who interacted with the non-adaptive version, there was no relationship between the perceived level of usability and learning outcomes.

6.4 Summary of Research Contributions

As specified in Section 1.5, several important contributions to the field of adaptive e-learning systems have been made by this study, and a number of research papers have already been presented at international conferences (see Section 1.6).

This work contributes by conducting a review of adaptive e-learning systems by considering different aspects related to the domain model, the learner model and the adaptation model [Alshammari et al. 2014]. The review also covered the issues of usability of adaptive e-learning systems and how they are evaluated.

Another contribution of this work arose from the proposal of an adaptive framework and the design and development of an adaptive e-learning system within that framework. The proposed framework does not differ very much from other models in related studies, but it is built with a focus on the field of adaptive e-learning systems. The framework is a conceptual model which can be used as a basis to design and develop a wide range of adaptive e-learning applications. Specific instances may adopt different approaches to learner, domain and adaptation models. As an instantiation of the framework, an adaptive e-learning system (AdaptLearn) has been designed and implemented. AdaptLearn can provide adaptation based on two learner characteristics including learning style and knowledge; it can be configured to provide adaptation based on each characteristic and in combination.

The major contribution of the present study relates to the experimental evaluation and data analysis of different forms of adaptation that are generated by AdaptLearn. This work differs from published research in two aspects. First, rigorous experimental design, careful investigation and precise reporting of results are features of all three experiments. Earlier work, with minor exceptions, lacks carefully designed experiments and uses small sample sizes [Akbulut and Cardak 2012; Truong 2016; Brown et al. 2009; Wolf 2007; Özyurt and Özyurt 2015]. A scientific approach was taken into account and formal hypotheses for each experiment were established so that they could be tested with empirical data and subsequent statistical analysis.

Second, this work is distinctive in incorporating two learner characteristics that are uniquely related to AdaptLearn: the information perception dimension of learning style and knowledge level. The findings clearly shed more light on the information perception dimension of the Felder-Silverman learning style model, and the experiments are among a very few that deal directly with this dimension, either as a single learner characteristic or in combination with knowledge level.

Taking into account the information perception dimension, in particular, also has the merit of offering a resolution to the ongoing debate in teaching between the exclusive application of either an abstract-to-concrete approach or a concrete-to-abstract approach. It provides a compromise by adopting a flexible approach that takes into account the learning style of each learner based on the information perception dimension of learning style. The findings demonstrate that meeting learners' characteristics enhances learning and learner satisfaction.

A contribution is also made to computer security education [Alshammari et al. 2015d]. There are a number of e-learning systems and tools that have been developed for that field. For example, Hu and Wang have introduced a virtual laboratory environment for computer security education; it allows students to perform different hands-on exercises [Hu and Wang 2008]. Tele-Lab IT Security is a tutoring system that provides different security exercises and tasks augmented with background concepts [Hu et al. 2004]. More innovative tools have also been proposed, such as the CyberCIEGE game; it supports the teaching of computer security in an engaging process [Cone et al. 2007]. Nevertheless, this thesis reports on one of the few studies concerning the application of adaptivity to this particular domain. It is expected that the results can, at least to some extent, be generalised to other computer security topics, such as data encryption standards and Kerberos protocols. Furthermore, since the proposed adaptive approaches effectively enhance learning and contribute to better computer security education, their application could also be beneficial in other computer science topics such as programming and databases.

The results of the experiments offer more evidence of the importance of personalisation and adaptation of learning material and its sequencing to meet the different needs of learners in e-learning systems. In particular, the results are related to the two characteristics integrated in the learner model of AdaptLearn, the information perception learning style and knowledge level.

6.5 Limitations and Lessons Learnt

This research has some limitations in terms of the system which was developed, experimental evaluations, matters related to learning style and general issues related to learning as a process.

In the AdaptLearn system, the contents of the domain model remained fixed throughout the provision of adaptivity, with learning material known beforehand. The system does not presently include the functionality to create and update the domain model using an authoring tool. However, the domain model was not the chief focus of this research and no contribution is claimed in this regard. The domain model was created simply to demonstrate one particular domain of the system related to computer security.

In terms of the learner model, learning style is taken into account. Learning style profiles were created using an assessment tool at the beginning of the interaction with the system and remained static. Coffield et al. categorise the Felder-Silverman learning style model used in the system as flexibly stable, indicating that, while learning style can be changed, that process occurs only over a long timeframe [Coffield et al. 2004]. Supporters of this learning style family argue that it is still possible to assess learning style using questionnaires and adapt learning material accordingly [Coffield et al. 2004; Graf et al. 2007]. Learning style was identified in this work, using the Index of Learning Style (ILS) questionnaire of the Felder-Silverman model. ILS was simplified down to a single dimension, the information perception or sensory-intuitive dimension. Several studies argue that ILS is considered a reliable and validated tool for learning style assessment, and that the dimensions of the Felder-Silverman model are independent from one another [Graf et al. 2007; Felder and Spurlin 2005; Zywno 2003]. Furthermore, the information perception dimension can be found in and is relevant to other learning style models such as Kolb and Myers-Briggs Indicator [Felder and Silverman 1988; Feldman et al. 2014]. Previous studies have also only used specific dimensions of learning style; the approach of incorporating and evaluating adaptation based on the information perception dimension remains comparable with those studies.

The other learner characteristic, learner knowledge, was initialised and maintained using tests and quizzes as the main interaction sources in AdaptLearn. In these tests, multiple-choice questions were used whereas different types of questions could have also been incorporated such as open-ended questions in order to increase the validity and reliability of the tests. Answers to this type of questions can be difficult to dynamically assess by the system; manual assessments of open-ended questions could be used but this is challenging and time-consuming when there are a large number of participants. Although tests are considered accurate measures in assessing and maintaining knowledge level and in providing adaptive feedback [Sitthiworachart et al. 2008; Brusilovsky and Millán 2007], other factors could have also been taken into account such as time spent, lessons studied and number of quizzes attempted. The issue is that more dynamic approaches to learner modelling require longer time periods of learner-system interaction before accurate and reliable models can be established and thus useful adaptation provided [Schiaffino et al. 2008; Graf 2007; Chrysafiadi and Virvou 2013b].

Although there were statistically significant findings in all three experiments, there were some limitations that must be acknowledged. In general, experimental evaluation can be affected by the Hawthorne effect (see Section 5.2.2). To eliminate its possible consequences, participants cannot be aware of being under formal observation in a study or of receiving special treatment. This phenomenon may have affected the findings of this work, because it was not possible to meet those requirements of a total lack of awareness. The experiments were designed to have control and experimental groups with double-blind and random assignment of participants in order to minimize this effect.

Another limitation is that all the experiments were short-term studies lasting approximately an hour; participants were all undergraduate students studying in a computer science programme, limiting the generalizability of this research. In addition, only a few learning objects were used in the experiments, and a larger number of learning objects to increase the amount of learning could have been incorporated. However, this would have added to the duration of the experiments, which may have encouraged participants not to complete them. The three experiments were satisfactory in terms of the sample size in comparison with previous studies. However, Experiment 1 was conducted with males only, while the sample makeup of Experiment 2 and Experiment 3 were heterogeneous in terms of gender. All these circumstances, however, could not have been avoided because of the limited resources at the time of conducting the experiments, in addition to the time and availability of participants.

Another problem that could affect the findings was the number of participants in the experiments, as revealed by the affinity with the sub-categories of the learning style dimension. A more refined adaptive approach could have also been used for a better fit with the sub-categories of the information perception dimension of learning style. For example, it may be more effective to treat learners differently according to their particular affinity with the mild, moderate or strong characteristics of a particular learning style. In the actual experiments, there were far more sensory learners than intuitive learners, and the majority of both had mild to moderate characteristics. Only a very few learners had strong characteristics. This finding largely agrees with several other related studies [Graf et al. 2007; Zywno 2003; Felder and Spurlin 2005].

Another important point was that the participants' controllability over the learning process in the experiments was limited; they had to follow the assigned tasks precisely and the system recommendations provided. These restrictions may not be faithful to the constructivist approach to learning, which emphasises the importance of learner controllability [Ertmer and Newby 1993]. Because of the nature of the controlled experiments, participants were asked to follow the system recommendations precisely in order to control the experiments and investigate the effectiveness of adaptation.

General issues related to learning must also be noted. Learning style represents only one learner characteristic. It is true that knowledge level has also been incorporated in the AdaptLearn system to provide adaptation. Other factors should not be ignored such as culture, personality traits, behaviour, affective state and learning experience, [Leontidis and Halatsis

2009; Martin and Briggs 1986; O'Regan 2003]. These factors can also contribute to the learning effectiveness and could be taken into account in future adaptive e-learning systems that incorporate different combinations of learner characteristics.

Brown states that "The nature of learning is obviously very complex, with a large interplay of factors" [Brown 2007]. As a result, there is a requirement for high-quality adaptive e-learning systems research with carefully designed and conducted experiments following sound models in educational theory. Many areas of computer science, including adaptive e-learning systems, take into account evaluation methodologies borrowed from social science and psychology, as much work is often carried out with people, who are of course the users of computer systems. Keppel provides a very useful guide to this type of research, covering issues related to experimental designs such as sample sizes, data collection tools, formulation of hypotheses and data analysis [Keppel 1991]. These points were taken into account to the fullest extent possible throughout this work as presented in this thesis.

6.6 Future Work

Several aspects of the present study, including the system developed and the experiments conducted, offer opportunities for future research.

Since the current work has some limitations identified in the previous section, addressing them in future research is important. It must be made clear that adaptation based on learning style is still a complex field despite the fact that significant results were obtained in this study when adapting learning material according to the information perception dimension of learning style. Since a single learning style dimension related to the Felder-Silverman model has been taken into account in this study; other dimensions of the model or possible other learning style models could also be incorporated. However, evaluating different aspects of learning style is challenging and requires a large number of participants given that a large number of learning style models have been developed, with each model having different dimensions that emphasise different factors. There may also be some overlaps between these models. Appropriate syntheses and an identification of relationships between these models and their associated dimensions have not yet been fully explored [Cassidy 2004].

Incorporating different learning style dimensions to provide adaptation is also challenging because some dimensions are more complex than others and adaptation based on specific dimensions may not always be beneficial. As an illustration of the complexity of some learning style dimension, such as the visual-verbal learning style, learning material can differ in their presentation and qualities when providing adaptation as visual learners interact with visual learning material only without being given the opportunity to interact with verbal material. This form of adaptation may not provide the opportunity for all learners to interact with other types of learning material to enrich their learning experience and understanding. In this work, the provision of adaptation based on the information perception dimension can eliminate this problem and the same learning material are provided for all learners but with different sequences to match their learning styles. Several important factors should be considered including justification and a careful selection of a learning style model and its related dimensions to be incorporated in an adaptive e-learning system, how adaptation can be provided according to these dimensions, and whether adaptation can enhance learning with minimal confounding factors following well-designed and robust experimental evaluations.

Another issue relates to the way that adaptation is provided for learners who have mild preferences with a particular learning style. As reported in Experiment 1, learners who have mild affinity with the information perception dimension of learning style in the matched group and the mismatched group had approximately the same learning outcome; they may not benefit from any type of adaptation; they may need to be supported by taking into account other learner characteristics such as their knowledge levels and motivation. This issue is still open and requires further investigation.

One possible approach to extend this work is to replicate the experiments with longer time horizons and larger sample sizes applied in different domains. For example, an adaptive e-learning system could be used and evaluated throughout a term or even a year of study in a specific course, rather than for a few hours. A long-term study may facilitate the creation of more accurate and dynamic learner models because learners would interact with the system for substantial time periods, and their behaviours and interactions with the systems could be monitored and updated continually. The type of learning style model incorporated in the majority of adaptive e-learning systems belongs to the flexibly stable family of learning style, which indicates that learning style is stable but can be changed over a long timeframe [Truong 2016], so dynamic learning style modelling based on learner behaviour with the system is potentially much more important in a long-term than in a short-term study [Chrysafiadi and Virvou 2013b; Graf 2007]. The same is true of modelling other learner characteristics such as learner knowledge and emotion. However, it is important to investigate the types of learner-system interaction data that can effectively be used to build dynamic learner models based on learning style and knowledge level; how can learning style and knowledge level be dynamically modelled in a way that more accurate and reliable learner models can be constructed, and how long does it need to build these models so that quick adaptation can be provided?

Based on the findings of Experiment 2, adaptation based on learning style and knowledge level yields significantly higher learning outcome and overall learner satisfaction than adaptation based on either single learner characteristic. This work can be extended by taking into account other factors such as affective state and motivation. The emotion and motivation effect of adaptation based on learning style and knowledge level can be investigated. These factors can also be integrated in an e-learning system to provide adaptation, and further experiments can be carried out to evaluate their learning effectiveness. Scant attention has been paid to the incorporation and evaluation of affective state, learning style and motivation into the learner model of adaptive e-learning systems [Chen and Sun 2012; Leontidis and Halatsis 2009; Martin and Briggs 1986; O'Regan 2003].

While the findings of this work were reported based on a quantitative methodological perspective, which was appropriate given the type of research questions and scientifically accepted measures of success, qualitative methods such as interviews and observations are also useful. To illustrate, Özyurt et al. used interviews with learners as a qualitative method to evaluate an adaptive e-learning system based on learning style; the results revealed positive opinions toward the form of adaptation provided [Özyurt et al. 2013]. In addition, observing learner behaviour when interacting with the system may unveil important information such as useful browsing patterns and preferences that might change across different domains. It is also important to note that such observation work should be planned very carefully, with pilot testing a necessary feature.

The proposed framework and the AdaptLearn system are open to further improvement and expansion that takes into account a wide variety of different yet relevant aspects of research. One direction is to investigate open learner modelling by facilitating the process for learners to inspect their own domain knowledge levels, learning styles and preferences, learning progress, course completion levels, prior knowledge and preferred materials to be studied. Such an open model may enhance the transparency and trust between the learner and the system, in addition to enhancing their metacognitive and self-directing skills [Bull and Kay 2010].

Another possible direction of research is investigating the effectiveness of adaptive gamification, in which different game-design elements such as point scoring, competition with peers, avatars and badges are incorporated into an e-learning system [Domínguez et al. 2013]. These techniques can be adapted according to learner behaviours, goals and interests. Another direction involves the incorporation and evaluation of social and collaborative learning features such as comments, rating, tagging, sharing, bookmarking and question-and-answer. Open learner modelling, adaptive gamification and social features can all be taken into account in an adaptive e-learning system. However, evaluating each aspect independently is vital for finalising a system that integrates all aspects. The final system as a functioning whole must also be evaluated very carefully.

The effectiveness of intelligent recommendation approaches, including content-based and collaborative filtering techniques, represents another important avenue of research [Klasnja-Milicevic et al. 2011]. Empirical evidence of their effectiveness in learning requires more research involving high-quality, carefully designed experiments [Klašnja-Milićević et al. 2015]. To illustrate, in a very simple view of a content-based approach, a learner may spend more time on examples on a specific topic, so the system may expect that the learner would prefer examples on different topics and provides recommendations accordingly. In a collaborative filtering approach, meanwhile, some learners may have similar patterns of behaviour when studying certain learning material using the system, so the system may predict what a particular learner may prefer based on the behaviour of similar learners. Finally, comparing the accuracy of different machine learning techniques such as Bayesian networks and case-based reasoning in learning style, learner knowledge and motivation modelling in a learner model could also be undertaken [Chrysafiadi and Virvou 2013b].

Adaptive and intelligent human agents can also be integrated into an e-learning system to mimic the idea of teaching with a one-on-one approach [Leontidis and Halatsis 2009]. Employing natural language processing and emotional intelligence can also further enhance human agents. For instance, an intelligent agent has the ability to express emotion, which could enhance the motivation, attitudes, perceptions and behaviours of the learner [Beale and Creed 2009].

6.7 Summary

This thesis has reviewed background research related to learning, e-learning systems and adaptivity. It has also offered an adaptive framework and designed and implemented an adaptive e-learning system called AdaptLearn within that framework. Three experiments were conducted concerning different forms of adaptation that are generated by AdaptLearn. The first experiment was concerned with the effectiveness of adaptation based on the information perception dimension of learning style. The second experiment investigated the effectiveness of the combination of the information perception dimension of learning style and knowledge level as two sources to generate adaptation. The third experiment examined the perceived usability level when providing adaptation, and its relationship to learning outcome.

The findings indicate that matching the sequence of learning material to the information perception dimension of learning style yields significantly better learning outcome and learner satisfaction than non-matching sequences. They also indicate that adaptation based on the combination of the information perception dimension of learning style and knowledge level yields significantly better learning outcome (both in the short- and long-term) and learner satisfaction than adaptation based on either single learner characteristic; this combination is also marked by a significantly higher level of perceived usability compared to a non-adaptive version of the e-learning system.

The three experiments revealed significant findings and offered more evidence for the importance of personalisation and adaptation of learning material and its sequencing to meet more precisely the learning styles and knowledge levels of learners in e-learning systems.

Appendix A: The Index of Learning Style

Questions related to the information perception dimension of learning style elicited from the Index of Learning Style questionnaire according to the Felder-Silverman model [Felder and Silverman 1988].

Question	Answer options
1. I would rather be considered	(a) realistic (b) innovative
2. If I were a teacher, I would rather teach a course	(a) that deals with facts and real life situations (b) that deals with ideas and theories
3. I find it easier	(a) to learn facts (b) to learn concepts
4. In reading nonfiction, I prefer	(a) something that teaches me new facts or tells me how to do something (b) something that gives me new ideas to think about
5. I prefer the idea of	(a) certainty (b) theory
6. I am more likely to be considered	(a) careful about the details of my work (b) creative about how to do my work
7. When I am reading for enjoyment, I like writers to	(a) clearly say what they mean (b) say things in creative, interesting ways
8. When I have to perform a task, I prefer to	(a) master one way of doing it (b) come up with new ways of doing it
9. I consider it higher praise to call someone	(a) sensible (b) imaginative
10. I prefer courses that emphasize	(a) concrete material (facts, data) (b) abstract material (concepts, theories)
11. When I am doing long calculations	(a) I tend to repeat all my steps and check my work carefully (b) I find checking my work tiresome and have to force myself to do it

Appendix B: Learner Satisfaction Questionnaire

The components of the Conceptualisation of e-Learner Satisfaction and their related questions [Wang 2003].

Component	Related questions
System interface	The e-learning system is easy to use. The e-learning system is user-friendly. The content provided by the e-learning system is easy to understand. The operation of the e-learning system is stable. The e-learning system makes it easy for you to find the content you need.
Learning content	The e-learning system provides up-to-date content. The e-learning system provides content that exactly fits your needs. The e-learning system provides sufficient content. The e-learning system provides useful content.
Personalisation	The e-learning system enables you to learn the content you need. The e-learning system enables you to choose what you want to learn. The e-learning system enables you to control your learning progress. The e-learning system records your learning progress and performance.

Appendix C: The System Usability Scale (SUS)

The items of the System Usability Scale [Brooke 1996].

No.	Item
1	I think that I would like to use this system frequently
2	I found the system unnecessarily complex
3	I thought the system was easy to use
4	I think that I would need the support of a technical person to be able to use this system
5	I found the various functions in this system were well integrated
6	I thought there was too much inconsistency in this system
7	I would imagine that most people would learn to use this system very quickly
8	I found the system very cumbersome to use
9	I felt very confident using the system
10	I needed to learn a lot of things before I could get going with this system

Appendix D: A Sample of the Test Questions

A sample of the pre-test, post-test and followUp-test questions.

Question	Answer options
Which is the main disadvantage of the Symmetric key encryption?	(a) More complex and therefore time-consuming calculations (b) The transmission of the cryptographic key (c) Less secure encryption function (d) It is not used any more (e) I do not know
If we use the key=3 to encrypt the word "*Birmingham*" using Caesar cipher. The cipher text will be:	(a) Eluokpijco (b) Eluplqjkdp (c) Eluqmrkleq (d) Eluqacefhj (e) I do not know
Alice (A) sends a message to Bob (B) consisting of a timestamp issued by Trent (T), session key, Bob's name and the message encrypted with Alice's key. Which mathematical equation represents this statement?	(a) $A \rightarrow B$: $E_K(S_T \mid B \mid K)$ (b) $A \rightarrow B$: $E_A(S_T \mid B \mid K)$ (c) $A \rightarrow B$: $E_B(S_T \mid K \mid B)$ (d) $A \rightarrow B$: $E_A(S_B \mid A \mid K)$ (e) I do not know
Why we need key-exchange protocols?	(a) Less complex and therefore less time-consuming calculations (b) To facilitate the transmission of the cryptographic keys (c) More secure encryption function (d) It is not used any more (e) I do not know
In your opinion of Caesar cipher, which sentence is true?	(a) It cannot be broken (b) It is hard to be broken (c) It can be broken easily (d) It depends on the used key (e) I do not know
In Asymmetric key encryption, the private key to decrypt messages is usually kept by	(a) sender (b) receiver (c) sender and receiver (d) all the connected devices to the network (e) I do not know
Identify which one is considered as a fundamental method of key-exchange protocols?	(a) Use a trusted third party (b) Generate random keys (c) Direct communication between parties (d) Out-of-band key exchange (e) I do not know

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